Determinants of Technological Innovation Adoption in Organizations -

An exploratory study on the example of Data Analytics

ABSTRACT

This master thesis investigates the specific determinants of technological innovation adoption on the example of data analytics by having three angles, namely the supplier, adopter and non-adopter perspective. By comparing two complementary innovation adoption frameworks with the empirical outcomes of technological innovation adoption, this thesis develops a new framework based on the findings. As there is little academic literature surrounding the topic of data analytics adoption in organizations, an inductive qualitative and exploratory design is conducted. The procedure of content analysis comprised two rounds of coding. In the discussion, five propositions are derived; To increase the likelihood of a technological innovation adoption, an internal, operational need of an organization; high levels of problem-solving thinking; short-term success stories; an independent digital unit as well as marketing activities of suppliers are required. Further quantitative research needs to be conducted to test the propositions as well as build potential theories.

Keywords: innovation adoption, technological innovation adoption, data analytics, determinants, drivers, barriers

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Max Julius Jacobi

i6151338

Double Degree Student

Supervisor Maastricht: Prof. Dr. Wilko Letterie

Supervisor Nova: Leid Zejnilović, Ph.D.

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List of Abbreviations

B2B	Business to Business
B2C	Business to Costumer
CEO	Chief Executive Officer
CIO	Chief Innovation Officer
CRM	Customer Relationship Management
DACH	Germany, Austria, Switzerland Region
EMEA	Europe, Middle East, Africa
GDP	Gross Domestic Product
POS	Point of Sale
RBV	Resource Based View
R&D	Research & Development
SaaS	Software as a Service
IoT	Internet of Things
I4.0	Industry 4.0

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1. Introduction

Nowadays, vast environmental changes and an increasingly complex world (McAfee & Brynjolfsson, 2012) occur due to globalization and developments in technology (Zukunftsinstitut, 2017). These changes have an impact on corporate strategies and thus, lead to an external innovation pressure on organizations (Porter, 2001). **Innovations** are not only driven by external factors but also by internal ones. An innovation might be a new product, service, production design or business segment (Tidd et al., 2005). Moreover, in order to service the changing needs of customers, innovations are a core necessity to remain stable in a market (Dodgson et al., 2008; Porter, 2001). Innovation can be academically divided into different types. Engelen et al. (2015) for instance, split innovation in technological, product-market and administrative innovation. Here, administrative innovation is related to controlling systems, product-market innovation focuses on product design, and technological innovation refers to the development in products and processes (Engelen et al., 2015).

In particular, **technological innovations** are currently highly relevant for organizations by virtue of trends such as digitalization and connectivity (Russom, 2011). Here, robotics, cloud computing, and autonomous driving are only a few key examples (Engelen et al., 2015). Moreover, Schumpeter highlights that organizations which thrive for technological innovations will accomplish a strategic advantage (Tidd et al., 2005). These statements are supported by several scholars such as Dodgson et al. (2008) who examine the management of technological innovations and Schramm (2017) who discusses the derivation and measurement of technological innovations. The amount of academic research surrounding technological innovation underlines its current theoretical relevance, while on the other hand, it highlights the practical importance (McKinsey, 2013).

Due to the practical importance, organizations aim to understand how to **adopt technological innovations** as the adoption is a critical factor in organizational productivity, competition, and survival (Howell, 1990). A technological innovation can be adopted externally or generated internally (Howell, 1990). Damanpour and Gopalakrishnan (1998) define adoption as an outside-in process that results in the incorporation of a product, service or technology that is new to an adopting business unit. This adopted innovation is generated and developed by an alternative organization (Damanpour & Gopalakrishnan, 1998).

In the 1970s, researchers such as Robertson and Bass focused on the differences between adoption and diffusion of innovations in organizations (Frambach, 2002). Additionally, Venkatesh and Bala (2008) investigated the managerial decision-making determinants about interventions that can lead to greater acceptance and effective utilization of IT based on the Technology Acceptance Model (TAM). Damanpour (1987) researched the adoption of technological, administrative and ancillary innovations of organizations, evaluating the correlation between these three factors.

Furthermore, by reviewing literature, determinants of innovation adoption have been researched with a focus on amongst others eco- or IT-innovations (Jansson et al., 2010, Venkatesh & Bala (2008). However, there is limited research with regard to the determinants of technological innovations adoption. To address this **research gap**, this thesis therefore aims to understand why some organizations choose to adopt technological innovations while others do not. In order to derive the specific technological innovation adoption determinants, this thesis compares the empirical findings about technological innovation adoption with two theoretical innovation adoption frameworks.

In the course of this thesis, **data analytics** has been used as an example of technological innovation adoption to make this abstract and wide-ranging topic more concrete. Due to the increase into new technological developments, the information which is to be collected and analyzed, has increased dramatically over recent years (McAfee & Brynjolfsson, 2012). These new technological tools expose new possibilities for managers, allowing them to make decisions based on data-driven evidence, rather than basing them on intuition (LaValle, 2011). Thus, for an organization, data analytics is perceived as a differentiator over its competitors (Erwin, 2017). Even though organizations might have realized the potential of data analytics, it however constitutes a particular challenge of adoption as it has a tremendous impact on the corporate business model (Russom, 2011). This is supported by a small number of application examples (Hamel, 2015; Pisano, 2015).

Researchers such as Gandomi (2015), Kambatla (2014), Zikopoulos (2012) provide a general overview surrounding big data and data analytics in their studies. Moreover, scholars such as Rahurkar et al. (2016), Bi & Cochran (2014) and Ma et al. (2014) researched data analytics in specific sectors such as the agricultural industry and also within the health industry. However, the adoption of data analytics is rarely academically discussed.

This thesis therefore aims to provide a profound investigation, based on the following **research question**:

What are the specific determinants of
technological innovation adoption in organizations?

The **remainder of this thesis** is structured as follows: First, the literature on innovation types, innovation adoption and its determinants are reviewed in order set the scene for the investigation of technological innovation adoption. The literature review highlights the importance of technological innovation adoption and classifies data analytics in particular as a major technological innovation. Thereafter, the method for this exploratory qualitative study is described. Subsequently, the results of the interviews are presented and discussed in order to derive propositions. Before the study is concluded, the implications for theory and practice as well as the limitations and avenues for future research are discussed.

2. Literature Review

2.1 Introduction

The objective of this chapter is to review literature in relation to the proposed research question in order to gather a theoretical perspective. After providing an overview of different innovation types, the determinants of innovation adoption, based on two complementary frameworks are explained. Subsequently, the focus is shifted onto the relevance of technological innovation adoption. In the end of the chapter, research questions are therefore deduced.

2.2 Different Innovation Types

Often, innovation is confused with invention (Tidd et al., 2005). By definition, **invention** is a "[...] promising product or service idea, based on new science or technology [...]" (Branscomb & Auerswald, 2002, p.1) while **innovation** is a "[...] successful entry of a new science or technology-based product into a particular market [...]" (Branscomb & Auerswald, 2002, p.1). More precisely, invention is about untargeted and non-economical driven basic research while innovation has a specific intention and an economical purpose (Godin, 2006; Ruttan, 1956). An innovation might be a new product, service, production design or business segment (Tidd et al., 2005). From a Schumpeterian perspective, every organization that strives for profits needs to innovate to ensure organizational change, growth and effectiveness (Damanpour & Schneider, 2008).

An innovation can be disruptive or sustaining (Christensen et al., 2000). By definition a **sustaining innovation** improves a product or service over time and consequently increases the value for a customer, as well as achieving higher margins for a company (Christensen et al., 2000). **Disruptive innovations**, however, create a completely new market through the launch of a new product or service. They are characterized by lower profit margins and might be inconsistent with the company's values (Christensen et al., 2000).

Innovation is academically defined in different ways and divided into various segments. Phillips and Phillips (1997) for example, splits innovation into **technological** and **non-technological** innovation. Here, innovative marketing strategies or organizational structures could be associated to non-technological innovations, while technological innovation comprises product and process innovation (Phillips & Phillips, 1997). Besides that, Engelen et al. (2015) divide innovation into technological, product-market and administrative innovation. **Administrative innovations** relate to management and controlling systems. **Product-market innovations** focus on product design, market research and innovations in promotion. **Technological innovations**, however, refer to research and development in products and processes (Engelen et al., 2015). By taking a profounder look, often innovation occur externally due to new supplied products on a market, but they are related to internal corporate processes too. This is why it is important to distinguish between different innovation segments (Engelen et al., 2015).
From chapter 2.5 onwards, there is a deep dive into technological innovations. Nonetheless, in the beginning of the literature review, a general overview can be found.

2.3 Adoption of Innovations

After introducing the literature on innovations, the adoption of innovation is reviewed. According to Damanpour and Gopalakrishnan (1998), there is a difference between the adoption and generation of an innovation in organizations. **Adoption** is defined as an outside-in process that results in the incorporation of a product, service or technology that is new to an adopting business unit. This adopted innovation is generated and developed by an alternative organization (Damanpour & Gopalakrishnan, 1998). **The generation** of an innovation includes the creation of an idea, the definition of a project, its design and development of the product or service, and additionally its marketing (Damanpour & Gopalakrishnan, 1998). As the decision to adopt an innovation tends to improve the effectiveness or performance of an organization (Damanpour & Schneider, 2006) this thesis concentrates on the adoption of innovations.

Even though, there is no standardized system or process to adopt an innovation that works for every organization and industry (Damanpour, 2008), scientists researched and defined various different **stages of adopting an innovation**. Rogers (1995, p.21) defines the innovation adoption decision in a comprehensive way as ‘‘a process through which an individual or other decision-making unit passes from first knowledge of an innovation, to forming an attitude towards the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision.” Others such as Aiken (1971) split the adoption process into evaluation, initiation, implementation and routinization. Zaltman (1973) defines the adoption decision into the following stages; knowledge awareness, attitudes formation, decision, initial implementation and sustained implementation. These diverse definitions can be combined into three general phases of the adoption of organizations, namely pre-adoption, adoption decision and post-adoption (Damanpour & Schneider, 2006; Rogers, 1995). The **pre-adoption** phase is characterized by the identification of a new need or the look for new solutions. Furthermore, in this stage, organizations create awareness for existing innovations, evaluating a suitable one, discussing it with other organization members (Damanpour & Schneider, 2006). In the **adoption decision** stage, the considerations are reflected by top managers from the technical, financial and strategic perspective in order to make a decision. If the idea or solution is accepted, the appropriated resources will therefore require allocation (Damanpour & Schneider, 2006). Lastly, the **post-adoption** stage is about a trial use, a possible necessary enhancement of the innovation as well as the preparation of the innovation by the members of the organization to ensure acceptance. After the adoption, the innovation becomes routine for the organization (Damanpour & Schneider, 2006, Porter, 1995).

2.4 Overview of Determinants of Innovation Adoption

After defining innovation adoption, the determinants of an innovation adoption are stated. This thesis focuses **on two complementary frameworks**, namely the macro and micro perspective of innovation adoption (Damanpour & Schneider, 2008). The **macro** perspective (figure 1) evaluates the objective characteristics such as actual costs, that facilitate or inhibit innovation adoption. This framework is developed by Damanpour and Schneider (2008). The **micro** perspective (figure 2), however, observes characteristics perceived by individuals of an organization that influence the adoption decision (e.g. perception costs). This framework is introduced by Frambach and Schillewaert (2002). By reviewing the macro and micro perspective, both are based on the same underlying basic concepts and need to be considered as supplementary.

Macro Perspective on Innovation Adoption

Describing the macro framework as stated in figure 1, Damanpour and Schneider (2008) focus on the interplay between objective innovation characteristics and the innovation adoption.

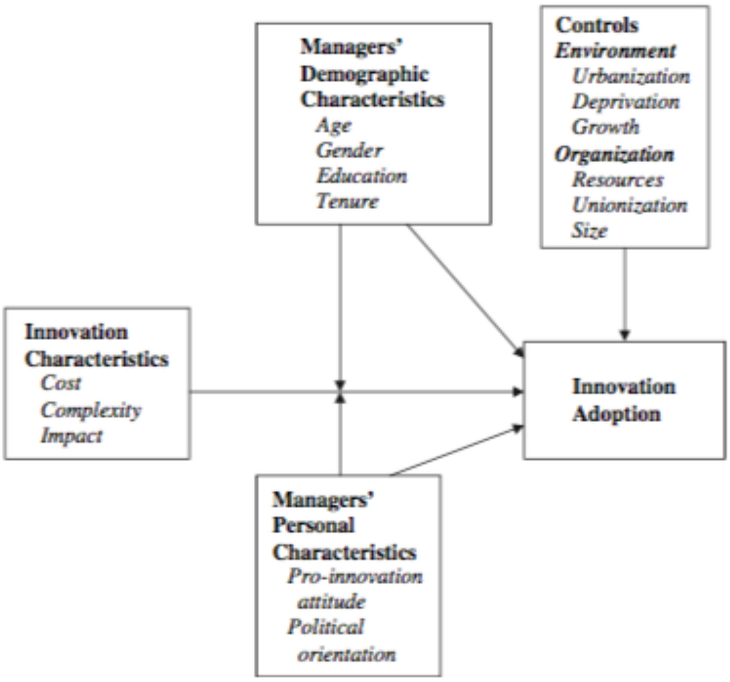

Figure 1: Macro Perspective: Characteristics of Innovation and Innovation Adoption (Damanpour & Schneider, 2008, p. 507)

They argue that the organizational adoption of an innovation is primarily influenced by the **innovation characteristics** costs, complexity and relative advantage (Damanpour & Schneider, 2008; Rogers, 1995). Here, Rogers (1995) states a negative relationship between costs and innovation adoption as the less expensive an innovation, the higher the probability of an adoption. However, Damanpour and Schneider (2008) found a positive direct effect within their framework. This surprising finding is assumed to be due to the type of innovation, namely administrative and incremental (Damanpour & Schneider, 2008). Innovation complexity is defined as the difficulty to understand and adopt an innovation. Complexity can be measured as the intellectual ability to understand as it is defined in low or high technological innovations. A second measurement of complexity is the originality or trialability of innovations. The higher the complexity and originality, the higher the aversion against the innovation. Thus, Damanpour and Gopalakrishnan (1994) argue that there is a negative correlation between complexity and adoption. In contrast, Damanpour and Schneider (2008) have no significant results. These two results might be affected by the type of innovation, too, namely administrative and incremental innovation (Damanpour & Schneider, 2008). Lastly, the impact is characterized as the economic profitability or relative advantage (Damanpour & Schneider, 2008). They both state that the greater the economic profitability of an innovation adoption, the higher the probability of an adoption. Here, they found significant results on innovation adoption.

Additionally, Damanpour and Schneider (2008) evaluate the managers' demographic and personal characteristics as a direct effect on the relationship between innovation characteristics and innovation adoption. Manager characteristics need to be taken into account in this framework due to the fact that they are playing an important role in an organizational adoption decision (Damanpour & Schneider, 2008; Howell & Higgins, 1990). Thus, there is a direct effect (Damanpour & Schneider, 2008). Analyzing the **managers' demographics**, it can be stated that they are researched intensively but only with incoherent results. Age for example might have a negative impact on innovation adoption as older managers tend to be less open-minded to new technologies and innovations (Huber et al., 1993). However, Damanpour and Schneider (2008) have not found a significant correlation. The tenure of a manager has a significant negative impact on innovation adoption (Damanpour & Schneider, 2008). A plausible explanation might be that the longer a manager is working for the same organization, the higher the possibility to have routines and thus an aversion to change and innovation (Damanpour & Schneider, 2008). Damanpour (2006) argues that education has a positive and enriching impact on innovation adoption as innovations entail knowledge and understanding. This statement could be supported by the research of Damanpour and Schneider (2008) due to the fact that managers feel more comfortable in such uncertain situations (Rogers, 1995). Furthermore, educated managers are more sensitive for the need of an innovation (Damanpour, 2006). The impact on innovation is highly discussed too in relation to gender, the last demographic characteristic. Some female managers tend to regard themselves as less innovative compared to their male managers. Damanpour and Schneider (2008), however, found a significant indicator that managers' gender is not related to innovation adoption.

Besides that, **personal characteristics** such as innovation attitude and political orientation need to be considered, too. According to Damanpour (1991; 2008), innovation attitude of managers has a significant positive influence on innovation adoption. This statement could be supported by the fact that these innovation-oriented managers are more likely to create a facilitating atmosphere which has a positive impact on organizational culture (Damanpour & Schneider, 2008). In contrast, Damanpour and Schneider (2008) could not find a significant result on the influence of a conservative or liberal orientation of the managers.

Micro Perspective on Innovation Adoption

Describing the micro framework as stated in figure 2**,** Frambach and Schillewaert (2002) aim to understand the determinants affecting the innovation adoption decision on an organizational level by incorporating several factors and multiple perspectives. While analyzing previous studies, the scholars provide a comprehensive framework.

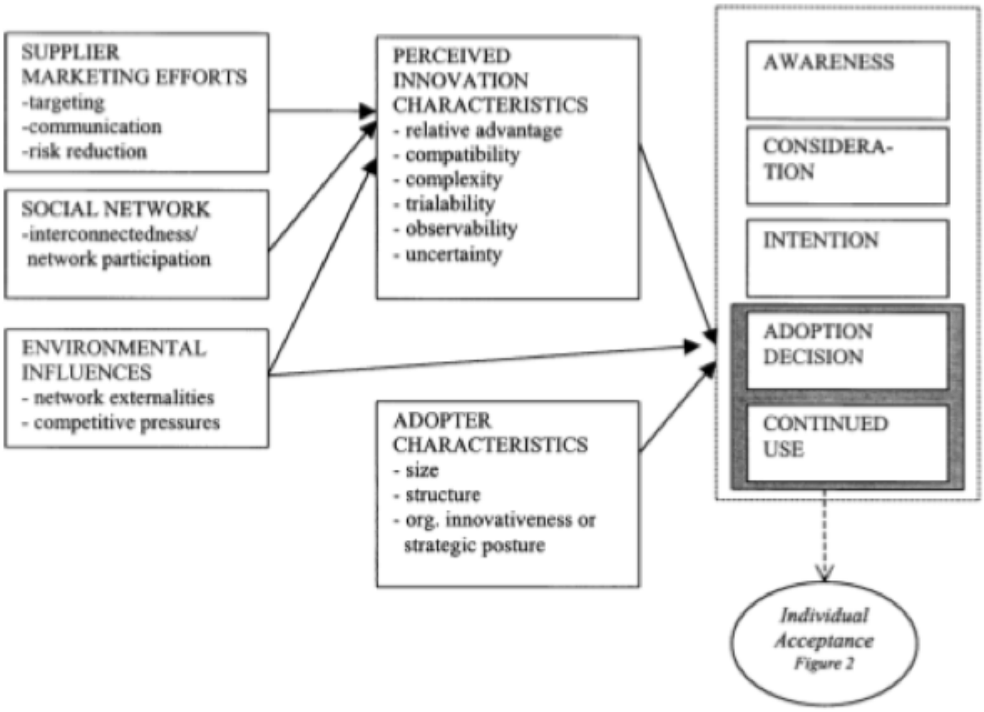

Figure 2: Micro Perspective: Determinants of the Adoption of Innovations (Frambach & Schillewaert, 2002, p.165)

The **perceived innovation characteristics** are in the center of this framework as they are influenced by other determinants but have a direct effect on the adoption decision. Perceived Information Characteristics are defined as parameters affecting the perceptions, evaluation and propensity of an innovation by members of an organization’s decision-making unit (Frambach & Schillewaert, 2002). Here, the economic advantage, compatibility, trialability, and observability have a significant positive influence on the adoption decision. The others have a negative impact on the adoption (Tidd et al., 2005).

According to Damanpour (1991), three **adopter characteristics** influence the adoption decision, namely the organization size, organization structure and organizational innovativeness. While, the positive or negative influence of the size is highly discussed, Frambach (2002) states that there is a positive relationship. Furthermore, the innovativeness of an organization has a positive impact. However, Frambach and Schillewaert (2002) found no significant results between the relationship of structure of an organization and innovation.

Supplier marketing activities have a direct positive relationship on the perceived innovation characteristics and thus, an indirect effect on the adoption decision. Here, three main factors are important, namely the accurate targeting of the selected adopters of an innovation, appropriate communication by the supplier in order to create awareness, as well as also influence the perception of an innovation adopter, and thirdly, the reduction of perceived risks such as operating or the financial risks for a potential customer (Frambach & Schillewaert, 2002).

Furthermore, the exchange between members within an informal **social network** might lead to a higher probability to adopt an innovation. Here, Frambach and Schillewaet (2002) assume a positively driven communication within one or multiple industries (Frambach & Schillewaert, 2002). In general, the higher the willingness to share information with others, the higher the interconnectedness (Frambach & Schillewaert, 2002; Roger, 1995).

Lastly, the **environmental influences** network externalities and competitive pressure, influence the adoption propensity. More precisely, a potential innovator might urge to adopt in case other business partners within its network have previously adopted an innovation. Furthermore, competitive pressure might lead to force organizations to adopt. However, this relationship cannot be clarified explicitly (Frambach & Schillewaert, 2002).

Based on these two innovation adoption frameworks, the following sub-research questions will be explored for the empirical analysis, with a large focus on technological innovation adoption:

- What are the specific determinants of technological innovation adoption compared to innovation adoption?
- What are the differences between adopters and non-adopters in terms of technological innovation adoption?

2.5 The Importance of Technological Innovation Adoption

Technological innovations enable **new technological standards** which trigger new products and services demanded by customers. These new products and services, however, lead to **new market entrants** and thus to a higher competition and a **decline in margins** for incumbents (Glicksman, 2017; Herrmann, 2010). These environmental changes accelerate the high pressure and importance of technological innovation adoption (McAfee & Brynjolfsson, 2012). Referring to the chapter 2.2, the relevance of technological innovation adoption compared to other types of innovations is stated. Of course, non-technological innovations such as innovative marketing strategies (Phillips, 1997) or administrative innovations including new management and controlling systems (Engelen et al., 2015) are important. Nonetheless, a majority of these innovations depend on technological standards (Herrmann, 2010). This highlights the **ubiquity of technological innovation** adoptions. These statements are supported by Rogers (1995) as technological innovations are perennial and thus a normal process. Recent examples of technological innovation adoption can be found in nearly every sector such as electronics, aerospace, pharmaceuticals, and information systems industries (Garcia & Catalone, 2002; Tidd et al., 2005). Key examples across the industry are autonomous driving (Heinrichs, 2015), cyber security (Von Solms & Van Niekerk, 2013), and radio frequency identification (Finkenzeller, 2010).

Based on the stated importance of technological innovation adoption, the following sub-research questions for the empirical analysis are deduced:

- What are the drivers of technological innovation adoption?
- What are the barriers of technological innovation adoption?
- What are the solutions of the barriers of technological innovation adoption?
- What are the differences in the technological innovation adoption between adopter and non-adopter?

2.6 Data Analytics as an example of Technological Innovation Adoption

New technological developments, for instance sensors or advanced computer science (Loebbecke & Picot, 2015), lead to various new opportunities for organizations as it might expand the corporate capabilities in nearly all departments and industries (Wagner & Finkelman, 2015). Due to these novel information technologies, the **variety** of data, the **volume** to collect information, and the **velocity** to analyze data has increased tremendously over the last years (McAfee & Brynjolfsson, 2012). These new technological tools enable **data analytics** (Erwin, 2017). Data analytics opens new possibilities for managers to make decisions based on data-driven evidence rather than on intuition (LaValle, 2011). This might differentiate incumbents from their competitors as data-driven companies tend to be more effective and efficient (LaValle et al., 2011; Tidd et al., 2005). Nonetheless, the adoption of data analytics constitutes an outstanding challenge due to a comprehensive impact on the corporate structures, economic uncertainty as well as operational bottlenecks (Erwin, 2017; Loebbecke & Picot, 2015; Russom, 2011).

In general, data analytics needs to distinguish itself from big data and data science. By definition **data science** is “the application of quantitative and qualitative methods to solve relevant problems and predict outcomes” (Waller & Fawcett, 2013, p.78). This implies that data science is the general term of data-driven techniques used when trying to extract insights and information from data (Waller & Fawcett, 2013). In other word, data science includes everything that is related to data cleansing, preparation, and analysis (Waller & Fawcett, 2013). **Big data** is defined as “very large, unstructured and fast-moving data” (Loebbecke & Picot, 2015, p. 150). McAfee and Brynjolfsson (2012) stress that big data is about the immense volume of data and begins with raw data that isn’t aggregated. An application example of big data in retail is the collection of customer data such as the use of mobile devices in stores (Waller & Fawcett, 2013). In a further step, **data analytics** add the analysis to big data as it structures and interprets information with the purpose to draw conclusions (Loebbecke & Picot, 2015). Data analytics enables insights from three different perspectives, namely descriptive, predictive, and prescriptive (LaValle et al., 2011). **Descriptive analytics** categorize data to analyze a corporate performance in terms of budgets, sales, or revenues. **Predictive analytics** exemplify historical data, detect patterns or relationships as well as derives and predicts future occurrences from these relationships to support a decision-making process (Cuzzocrea et al., 2011; Erwin, 2017). Predictive analytics therefore predict relationships not readily apparent with traditional analyses (LaValle et al., 2011). **Prescriptive analytics** enable mathematical algorithms to determine and derive alternative decisions that involve objectives comprised of high volume and complexity (Cuzzocrea et al., 2011; Erwin, 2017).

Caused by the comprehensive impact of data analytics on organizations and the accomplishment to enhance products and processes (Engelen et al., 2015; Erwin, 2017), this thesis records data analytics as an example of technological innovations.

The **prime example** of extremely successful adopting data analytics in an organization is **UPS**. This logistics company collects data of its fleet, more precisely it's fleet's speed, direction, braking and driving performance. By doing so, UPS is able to optimize and restructure the routes of its drivers in real time with the support of a cloud solution. This led to savings of 8.4 million gallons of fuel and a cut of 85 million miles until 2011. Due to this accomplishment, UPS additionally started to apply this initiative for its aircrafts as well (SAS Institute, p.4, 2013). Further non-sector specific application examples include the reduction of downtimes through predictive maintenance or online customized advertising activities (Erwin, 2017).

3. Methodology

3.1 Introduction

The objective of this chapter is to provide a greater understanding of the determinants of adopting a technological innovation on the example of data analytics. An inductive analysis including conducted in-depth interviews with supplier, adopters and non-adopters of data analytics was taken to answer the research questions.

3.2 Research Design

After conducting comprehensive online and offline research, it can be stated that there is little academic literature surrounding the topic of data analytics adoption in organizations. Therefore, according to Yin (2016) and Burns and Burns (2008), an inductive qualitative and exploratory design is the most appropriate while analyzing the underlying theory of innovation adoption in general.

Qualitative findings are defined as characteristics rather than numbers which aim to understand and describe knowledge and experiences of humans. Furthermore, this approach is used to allocate new and primary information from a specific focus group (Yin, 2016). Qualitative research methods take complex circumstances into consideration as the evaluator can realize the motivation, needs and pressures of humans. In addition, this approach is required as a preliminary to quantitative studies, which is fundamental when forming a hypothesis (Burns & Burns, 2008; Yin, 2016).

Furthermore, the empirical element is an **inductive** process. More precisely, it starts with a specific observation, followed by an analysis that produces explanations of the observations. The intention is to identify patterns inside the organizations. Thus, this thesis has a proposition-generating approach, rather than a hypothesis-testing approach (Yin, 2016), aiming to build a bridge from qualitative to deductive researches (Eisenhardt, 2007).

3.3 Data Collection

In-depth interviews support an inductive exploratory approach in order to gather insightful and comprehensive information surrounding the adoption decision of technological innovations (Yin, 2016). The underlying **questionnaire** (appendix 2-4) was structured as follows: formal introduction, demographic questions, body of study, and expression of thanks (Yin, 2016). More precisely, in the beginning of the questionnaire, general questions about technological innovation were asked, while afterwards the focus was on data analytics. The questionnaire includes open-ended questions and is based on the stated research questions. These are questions "that permit the respondent to supply their individualized response" (Burns & Burns, 2008, p. 497). After introducing the purpose of the interview, it is important that the interviewer does not provide too much information about the study. This would cause a bias within the survey. Furthermore, as five interviews are conducted, it is necessary to ask the same questions in the same order. The wording of the questions needs to be simple, precise and specific (Burns & Burns, 2008).

One advantage of conducting in-depth interviews is the flexibility. The researcher is able to observe the whole environment. Additionally, questions can be repeated and clarified. By doing so, misunderstandings can be avoided (Burns & Burns, 2008; Yin, 2016). Another advantage is a high response rate as potential interviewees are more willing to talk than to write an answer (Yin, 2016). Fourthly, interviews are needed when extensive data is required on complex subjects. Here, comprehensive and precise responses are a benefit (Burns & Burns, 2008).

The **interviews are conducted** personally or via Skype and are audio-recorded as well as professionally transcribed within one day. The interviewees are German. Thus, the interviews are conducted in their mother tongue in order to avoid misinterpretations. Nonetheless, the coding is implemented in English. The questionnaires are sent in advance in order to ensure a high quality and efficient meeting. On average, an interview lasts for 30-40 minutes.

In order to ensure that the academic data is collected sufficiently, a **triangulation** of gathering data is conducted (Yin, 2016). In addition to academic literature and personal interviews, newspaper articles are also collected. By doing so, an independent and objective data collection and research study can be concluded (Yin, 2016)

3.4 Data Analysis

In this chapter, the analytic process and procedure is stated in order to evaluate the credibility of the findings. Therefore, after conducting five in-depth interviews, the coding and classification of the findings is stated.

In the beginning, a line-by-line analysis through the interview responses was conducted in order to discover collective statements, a variety of categories as well as initial codes (Yin, 2016). According to Burns and Burns (2008), conceptual categories are based on amongst others causes, consequences, or hierarchies. In the beginning of the coding procedure the complete responses are read while variations and relationships are searched afterwards to identify and cluster codes (Yin, 2016). The procedure of content analysis comprised two rounds of coding as after the **first reduction**, the conceptualization and category development does not lead to the desired outcome caused by too precise and subtle themes. The **second reduction** therefore redefined the coding according to the evolving understanding towards more conceptual codes (Yin, 2016). For example, during the first coding process, the initial code "high error rates" was found, while in the second round, the code was redefined in "operating determinants". Thus, the findings were structured and classified in an enhanced way. By doing so, a thematic approach was ensured (Yin, 2016).

3.5 Case Selection Criteria and Introduction of Interviewees

The master thesis includes **five in-depth interviews**, more precisely one supplier, two adopters and two non-adopters of data analytics. By doing so, the thesis examines the research question from three alternative angles. An overview of the interviewees can be found in figure 3.

Category	Supplier	Adopter		Non-Adopter	
Company	Google Germany	Konditorei Junge	Weil Engineering	Süverkrüp+Ahrendt	Sievers Sanitär
Interviewee	Jens Redmer	Gerd Hofrichter	Florian Weil	Dr. Wolf-Dieter Niemann	Christian Sievers
Position of Interviewee	Principal of New Products Department	Director of Communication	Project Manager Industry 4.0	CEO	CEO

Figure 3: Overview of Interviewees

The selection of the interviewees is based on several **parameters**. Firstly, the adopters and non-adopters are not forced to invest in data analytics. Thus, a holistic investigation and understanding of the decision to adopt or not adopt data analytics is possible. Secondly, the selected companies are hidden champions within their industry which implies a major role and therefore provides insightful information. Moreover, according to Albert et al. (2016), the interviewed companies belong to one of the biggest industries in Germany, that is the production and also retail sector. Lastly, referring to the key informant approach (Marshall, 1996), only high ranked employees are interviewed, namely two CEOs and three top managers.

Google Germany GmbH is the **supplier** of data analytics. The supplier ensures an experienced and objective perspective of the adoption decision. Google Germany GmbH is a subsidiary of Alphabet Inc. which is based in Silicon Valley, USA (Redmer, 2017). Google, which is mainly known for its internet search engine, provides data analytics tools such as data reporting, analyzing, and visualization software. The organization aims to diffuse their products in the next years (Redmer, 2017). For Google Germany GmbH, Jens Redmer, Principal in the New Products department, will provide important and sophisticated information. He is a long-time expert in this sector and has worked for Google Germany for 15 years (Redmer, 2017).

Salesforce.com Inc. confirmed to provide insights as a second supplier of data analytics on the 6th of November 2017. However, the contact person was not reachable.

On the **adopter** side, Weil Engineering GmbH and Konditorei Junge GmbH provided their insights and information. **Konditorei Junge GmbH** was found in 1897 and is currently one of the biggest bakeries in Northern Germany with 190 stores and 3700 employees (Hofrichter, 2017). Throughout the long company history, the management suffered many challenges. Based on these experiences, the CEO Axel Junge is aware of the importance of new development adoptions. The organization tries to be an innovator and learn from other industries (Hofrichter, 2017). By doing so, they revolutionized their internal ordering process of bread and sandwiches. Since a few years, different variables with the support of data analytics are responsible for the order process of bread and sandwiches (Hofrichter, 2017). Gerd Hofrichter, the director of communication, provides insights surrounding the company and their project (Hofrichter, 2017).

The second **adopter** of data analytics is **Weil Engineering GmbH**. The company is based in Müllheim, Germany and is the market and technology leading manufacturer for high-tech roll forming and welding machines since 1987 (Weil, 2017). The local orientated company has further service divisions in the United States and Shanghai, China, and is a member of a global network. The company employs 220 people and mainly provides its products and services to the automotive and ventilation technology sector (Weil, 2017). Especially in the global business, innovations are of a high demand in order to sustain a competitive advantage. Recently, the company adopted a cloud-based service solution to increase its service standards (Weil, 2017). Florian Weil, the oldest son of the current CEO Wolfgang Weil participated in the interview. Florian Weil graduated with a master's in engineering from RWTH Aachen, Germany and started to work as a project manager Industry 4.0 at Weil Engineering (Weil, 2017).

On the **non-adopter** side, interviews with Süverkrüp+Ahrendt GmbH & Co. KG and Sievers Sanitär GmbH are conducted**. Süverkrüp+Ahrendt** is based in Neumünster, Germany and has a company history dating back 100 years. The company has several car dealer offices in the northern part of Germany and distributes new, used and commercial Mercedes Benz vehicles (Dr. Niemann, 2017). Currently, they have 40,000 customers, roughly 400 employees. Süverkrüp+Ahrendt has barely adopted technological innovation projects even though they might be interested in novel innovations (Dr. Niemann). The interview is conducted with the CEO Dr. Wolf-Dieter Niemann. He is responsible for the strategic development of the company (Dr. Niemann, 2017).

The second **non-adopter** of data analytics is **Sievers Sanitär GmbH**. The company is based in Kiel, Germany. The organization supplies services in heating, sanitary, solar and ventilation and has not invested nor planned to invest in technological innovation (Sievers, 2017). However, Sievers Sanitär collects data manually for internal purposes. The corporation employs 31 individuals including 12 apprentices and is a local leader, consequently representing smaller, non-digitalized organizations (Sievers, 2017). The interview is conducted with the CEO Christian Sievers.

4. Results & Findings

In this chapter, differences and similarities of the statements of the interviewees are discussed. An overview of the findings can be found in the appendix 1. The findings are stated in sections, more precisely the interview questions are presented successively in the order supplier, adopter, and non-adopter. In the end of each section, a tabular overview of the findings is constituted.

Starting the interview with the **determinants of technological innovation adoption**, it can be stated that the **supplier** Google underlines the importance to hire sophisticated employees first, who then define and develop new technological innovation adoption projects (Redmer, 2017). Organizations which do this the other way around, might not be able to become an advanced, sophisticated, and innovative organization. Besides hiring strategies, it is crucial to have employees with the right capabilities who are willing to be educated and developed, too (Redmer, 2017). Furthermore, Redmer (2017) underlines that it is important to have a short adoption process. This includes extremely high efforts and a collaboration of all departments within the organizations (Redmer, 2017).

On the **adopter** side, Weil (2017) applies a customer centric approach to ensure a successful adoption. In case of a new contract including a technological barrier, the organization defines and analyzes first, whether the development of a new technological innovation has a potential market. If this could be affirmed, there are three stages, namely a definition, technological and conceptual one. These stages are used pyramidal with the definition as a basis. This process is characterized by a trial and error principle including prototyping and feedback loops. Thus, a customer centric as well as trial and error approach are drivers of technological innovation adoption (Weil, 2017). By doing so, Weil (2017) supports Redmer in terms of the importance of a close collaboration of the R&D and sales department. Here, the managers' commitment is indispensable even though it might require considerable effort (Weil, 2017).

For the **non-adopter** Sievers (2017), a chronological analysis of a potential market size and target group is key before adopting technological innovation. If the organization analyses a demand for a technological innovation, Sievers (2017) need to adopt the processes internally to enable sufficient capacities for the required innovations. Here, capable employees are crucial (Sievers, 2017) as highlighted by the adopter and supplier. This determinant is supported by the second non-adopter Dr. Niemann (2017). In general, operating capacities are at a bottleneck for a lot of companies which constitutes a barrier of technological innovations (Dr. Niemann, 2017).

In figure 4, there is an overview of all statements of the interviewees regarding the determinants of technological innovation adoption.

		Theme	Statement
Supplier	Google Germany	Operational Capacity	Recruitment of highly qualified employees which define new projects, not v.v.
		People	Management which supports and anticipates innovation
		Process Approach	Trial and Error Culture
		Operational Capacity	Short Adoption Processes
Adopter	Weil Engineering	Operational Determinants	Close collaboration of R&D and sales department
		Process Approach	Customer centric approach to identify new needs
		Process Approach	Adoption stages: definition, market analysis, technological requirements, concept and prototyping stage
		Process Approach	Trial and Error Culture
Non-Adopter	Süverkrüp+Ahrendt	Operational Capacity	Need to create new resource capacities for innovations
		Operational Capacity	Sufficient skilled employees
		Operational Capacity	Recruitment of new employees if no capacities
		Operational Determinants	Efficient collaboration of departments
		Technology	Technological capabilities insufficient in the company for a successful adoption process
	Sievers Sanitär	Operational Capacity	Chronological and analytical way how to adopt an innovation
		Strategic Determinants	Analyze market and targets before investing
		Process Approach	Adapt internal processes to enable innovations
		Operational Capacity	Skilled and capable employees
		Operational Determinants	Support through third parties such as suppliers

Figure 4: Overview of all Determinants of Technological Innovation Adoption

In the second question of the interview, **the reasons for (not) adopting data analytics** are stated. The **supplier** Redmer (2017) states that generally data analytics is nothing novel, however, the organizations do not know where and how to start. In case, companies develop a strategy, they might face several benefits such as higher levels of efficiency through enhanced technologies and thus higher competitiveness.

On the **adopter** side, Konditorei Junge adopted data analytics tools in order to reduce the bad planning of bread and sandwich orders and to achieve economies of scale (Hofrichter, 2017). Therefore, the company developed a centralistic order system based on different indicators such as the day or weather. In the past, each branch manager was responsible for his or her bread and sandwich orders. These orders are based on historical values or the personal instinct. However, today everything is managed and supervised by a central information system. This central system is developed by the company itself and run by 20 IT employees (Hofrichter, 2017). Furthermore, Junge realized that this information system can be complemented by additional features such as a system that manages the opening hours of all stores and orders the required non-food materials, such as paper cups and napkins (Hofrichter, 2017). Weil Engineering adopted data analytics to reduce production and labor costs, while simultaneously increasing the complexity of handling the machines even with a lack of skilled employees (Weil, 2017). The company therefore deploys sensors on their machines in order to report specific information to a cloud solution. After a sensor reports an error, computers analyze why this sensor is triggered. If this sensor is triggered by problem of a machine, the organization can help its customers immediately. Moreover, Weil Engineering is able to even predict a specific service without human interaction (Weil, 2017). Weil (2017) mentions as an example, that often customers do not know the real occupancy rate of its machines and thus there are wrong maintenance frequencies. However, with sensors and a cloud solution, Weil Engineering can determine the exact operating time and consequently predict the next service (Weil, 2017).

But most importantly, while reporting information of sensors, this new gained knowledge enables the company to make conclusions for further technological innovations (Weil, 2017).

Süverkrüp+Ahrendt and Sievers Sanitär **have not chosen to adopt data analytics**. For Süverkrüp+Ahrendt, the main reason for not adopting data analytics is the limitation of operating capacities. The franchisee of Mercedes Benz is generally interested in a lot of technological innovations such as data analytics but due to a lack of operating capacities, the company prioritizes other more urgent projects (Dr. Niemann, 2017). Furthermore, Süverkrüp+Ahrendt is currently concentrating on the preparation and restructuring of internal data. According to Dr. Niemann (2017), this is a fundamental requirement before adopting data analytics. Additionally, besides concerns about the legal procurement of information, Sievers Sanitär highlights that there is no need to adopt such cost and time-consuming innovations. Currently, the organization is growing and there is no external nor internal pressure. An adoption is not mandatory (Sievers, 2017).

In figure 5, there is an overview of all statements of the interviewees regarding the reasons for (not) adopting data analytics. The red boxes are reasons for no adoption, while the green ones are reasons for adoption.

		Theme	Statement
Supplier	**Google Germany**	Operational Capacity	Companies do not know where and how to start
		Technology	Collection of data nothing innovative but lower barriers of entry and higher technological standards
		Strategic Determinants	Several benefits such as maintain competitiveness and increase in efficiency
		Technology	Higher efficiency through better technological tools
Adopter	**Konditorei Junge**	Operational Determinants	Reduce misplanning of bread and sandwich orders
		Strategic Determinants	Restructuring of branches to categories with the support of a central information system
		Strategic Determinants	New competitors: e.g. Amazon Fresh
	Weil Engineering	Operational Capacity	Insufficient skilled employees
		Technology	Operation of machines is becoming more complex, as the systems are more complex
		Operational Determinants	High labor costs
		Operational Determinants	High production costs
Non-Adopter	**Süverkrüp+Ahrendt**	Strategic Determinants	Dependency on Mercedes Benz
		Operational Determinants	First, structuring internal data, then data analytics adoption
		Operational Determinants	Other operating priorities
		Strategic Determinants	No competitive pressure to adopt
	Sievers Sanitär	Strategic Determinants	Missing own experience
		Strategic Determinants	Missing market experience
		Technology	No network or community to get information
		Strategic Determinants	No need to adopt

Figure 5: Overview of all Reasons for (not) adopting Data Analytics

After understanding the reasons for (not) adopting, the **drivers of data analytics** need to be stated. Here, the drivers can be classified by internal and external factors. From the **supplier** perspective of Google, their customers benefit internally from a better understanding of operating processes and enhanced product solutions, as well as externally from new business markets and services solutions (Redmer, 2017). To explain the drivers of data analytics adoption, Redmer (2017) states the case of the agriculture machinery manufacturer, John Deere. John Deere deploys sensors on their agriculture machineries in order to document different characteristics such as abrasion. By doing so, the company is able to predict the possibility of a service and can therefore schedule an appointment with their clients in advance. In the past, clients called their machinery suppliers when they had the need for a service. Caused by this technological innovation, John Deere changed their business model from a reactive to a proactive approach and is now able to predict a service demand. Therefore, John Deere is no longer thinking about how to shorten the reaction period for a service, but rather trying to prevent services. Moreover, the company acquired several new insights regarding their machineries. Examples are better insights about service intervals or the ability to exhaust new services (Redmer, 2017).

The **adopter** Konditorei Junge experienced a minimization of errors particularly in order planning after the adoption of the cloud-based system. Moreover, the organization aims to shorten the communication channels (Hofrichter, 2017). Furthermore, the company benefits from a new source of data generation through a prepaid customer loyalty card. By doing so, Junge strengthen the market competiveness and increased the innovation pressure on it's competitors, while investing in data analytics (Hofrichter, 2017). Weil Engineering benefits both internally and externally, too. While ensuring a higher quality of data which leads to a better fundament for a decision-making process, the services for customers increase simultaneously. Furthermore, Weil (2017) underlines that the company has the opportunity to sell this knowledge about data analytics to other companies. This possibility is stated by Hofrichter (2017), too.

The **non-adopter** Sievers (2017) stresses that data analytics might be important for the internal use. Here, a higher transparency of internal processes and resources or the improvement of the control of occupancy rates could lead to better decision-making processes. Here, Dr. Niemann (2017) addresses the potential benefit of an optimized internal supply chain.

Thus, it can be stated that non-adopters recognize mainly internal opportunities while adopters indicate both external and internal drivers. Furthermore, supplier and adopters stress an extensive range of opportunities while the non-adopters are more restricted.

In figure 6, there is an overview of all statements of the interviewees regarding the drivers of data analytics adoption.

		Theme	Statements
Supplier	Google Germany	Strategic Determinants	Open new business markets
		Operational Determinants	Optimize services, predictive services
		Operational Determinants	Better understanding of internal processes to derive actions
		Strategic Determinants	Change business model disruptively and sustainably for the future
Adopter	Konditorei Junge	Operational Determinants	Minimize errors of order planning
		Technology	Gathering more data about customers through prepaid loyalty card
		Strategic Determinants	Being first mover increases pressure for competitors
		Strategic Determinants	Strengthen market competiveness
	Weil Engineering	Operational Determinants	Minimize errors of checklists
		Operational Determinants	Adapt solutions and knowledge to other machines
		Technology	Better data to derive decisions
		Strategic Determinants	Sell knowledge about cloud solutions to others
Non-Adopter	Süverkrüp+Ahrendt	Operational Determinants	Legal generation of data about customers
		Strategic Determinants	Better understanding of customers' needs
		Technology	Support decision-making process
		Operational Determinants	Improve and optimize internal supply chain
	Sievers Sanitär	Operational Determinants	Higher transparency about internal processes and resources
		Operational Capacity	Better use of resources (budget, employees)
		Operational Determinants	Better control of occupancy rates
		Technology	Improve general decision-making

Figure 6: Overview of all Drivers of Data Analytics Adoption

By getting a profound understanding of the adoption **barriers of data analytics**, it can be stated that supplier, adopters and non-adopters predominantly identify the same barriers. Starting with the **supplier** Google, Redmer (2017) highlights a lack of management capabilities. Often, top managers are not willing to adopt or do not understand the purpose of a technological innovation. This might lead to an underestimation regarding the urgency of adopting data analytics adoptions (Redmer, 2017). Additionally, employees are missing a sufficient digital education too, as many companies have not invested in their current or future employees, yet (Redmer, 2017).

On the **adopter** side, Weil (2017) agrees and adds that it is not only the managers that act as a barrier but also the workforce which fears changes in their working environment, potentially possessing an aversion against technological innovations. Moreover, the investment costs are unforeseeable which leads to the fact that especially in the short run, costs are undoubtedly higher than the benefits (Hofrichter, 2017). This might annoy impatient top managers (Hofrichter, 2017). Furthermore, according to Weil (2017), it is not easy to identify and select the relevant data and unveil the added value for the company or a client. Lastly, the corporate culture might be a potential barrier, too. Caused by grown corporate structures which might be somewhat conservative, organizations tend to not provide a perfect environment to support innovations compared to start-ups (Hofrichter, 2017).

The interviewees of **non-adopters** agree on the supplier and adopter statements. Managers have reservations and fears of contact of data analytics, supplemented by a lack of understanding of data analytics (Dr. Niemann, 2017; Sievers, 2017). Sievers (2017) adds that the benefits of data analytics are economically difficult to measure. Thus, there is no real economic reason to adopt. Furthermore, the organizations do not know how and where to start as they do not know the suppliers for technological solutions (Dr. Niemann, 2017; Sievers,2017).

In figure 7, there is an overview of all statements of the interviewees regarding the barriers of data analytics adoption.

		Theme	Statements
Supplier	**Google Germany**	Operational Capacity	Lack of digital education of employees biggest adoption barrier
		People	Underestimation of innovation pressure of top managers
		People	No willingness to change a business model
		People	Lack of management capabilities, do not know where and how to start
Adopter	**Konditorei Junge**	Strategic Determinants	No real economic proof of benefits
		Operational Determinants	Grown and inflexible corporate structures vs. Start-Up stuctures
		Operational Determinants	Conservative corporate culture which includes an aversion to innovations
		People	Lack of data analytics understanding
	Weil Engineering	Process Approach	Badly structured and non-digitalized processes
		Operational Capacity	Which data/What is the value/Where to source?
		Technology	Missing measurement unit standards
		People	Different backgrounds of employees which avoid changes in their routines
Non-Adopter	**Süverkrüp+Ahrendt**	People	Workforce fears changes and try to avoid technological innovation
		Strategic Determinants	Automotive suppliers own the generated data
		People	Missing data analytics understanding of top managers
		Operational Capacity	Lack of human capacities
		Strategic Determinants	No real economic pressure to invest
	Sievers Sanitär	People	Employees have reservations and fears of contact with innovations
		Operational Capacity	Lack of knowledge on how and where to gather data and information
		Operational Capacity	Lack of knowledge about suppliers of Data Analytics to start adoption
		Strategic Determinants	High adoption costs --> No real economic proof of benefits
		Operational Capacity	No operating capabities

Figure 7: Overview of all Barriers of Data Analytics Adoption

Towards the end of the interview, the interviewees stated the **solutions of the adoption barriers of technological innovation adoption**. According to the **supplier** Redmer (2017), time is a crucial determinant to solve barriers as managers and employees need a period to understand data analytics, educate the workforce towards data analytics and change the mindset of a business culture towards an open-minded interaction. Furthermore, it is key that managers are willing to change a business model and commit to a new technological adoption (Redmer, 2017).

According to the **adopter** Konditorei Junge, it is essential to apprehend that data analytics adoptions require a holistic approach and affect the whole supply chain. Here, the collaboration of all departments might be a solution (Hofrichter, 2017). In addition, he encourages organizations to create an independent “digital unit” which defines and thrives upon new innovation projects (Hofrichter, 2017). The independency of this unit is highly important due to the fact that managers or other operating priorities might affect and inhibit the growth of the “digital unit” (Hofrichter, 2017). Weil (2017) adds the need of a failure culture. This indicates that employees are permitted to examine something out of the box without consequences. Here, a workshop approach enables employees to engage in the trial and error of novel solutions.

From a **non-adopter** perspective, the creation of an online or offline community might provide suppliers, adopters, and non-adopters a platform to share experiences and encourage members to understand the different perspectives (Sievers, 2017). Dr. Niemann emphasizes the importance to improve the internal collaboration within the departments. Additionally, the interaction with the franchisor needs to be enhanced. By doing so, new operating capacities for technological innovation adoption are becoming available.

To sum up, it can be noticed that the adopters mention more precise solutions while the non-adopter are constrained. In figure 8, there is an overview of all statements of the interviewees regarding the solutions of the barriers of data analytics adoption.

		Theme	Statement
Supplier	Google Germany	Process Approach	Provide time for culture change
Supplier	Google Germany	People	Willingness to change a business model + technology understanding
Supplier	Google Germany	Process Approach	Trail and error culture and Innovation Lab
Supplier	Google Germany	Operational Capacity	Invest in own workforce towards advanced and sophisticated employees
Adopter	Konditorei Junge	People	Have short-term success stories during the adoption process
Adopter	Konditorei Junge	People	Management supports and leads adoptions
Adopter	Konditorei Junge	People	Willingness to adopt Data Analytics holistically
Adopter	Konditorei Junge	Process Approach	Creation of independant "digital unit"
Adopter	Weil Engineering	Process Approach	First, structure processes, then digitalization
Adopter	Weil Engineering	Process Approach	Workshops with employees which define projects to great acceptance
Adopter	Weil Engineering	Process Approach	Prototyping based on trial and error
Adopter	Weil Engineering	People	Have short-term success stories
Non-Adopter	Süverkrüp+Ahrendt	People	Be open-minded for new developments and innovations
Non-Adopter	Süverkrüp+Ahrendt	Strategic Determinants	Reinvest profits internally (e.g. in processes and employees)
Non-Adopter	Süverkrüp+Ahrendt	Strategic Determinants	Improve collaboration with Mercedes Benz
Non-Adopter	Süverkrüp+Ahrendt	Operational Determinants	Improve internal collaboration within departments
Non-Adopter	Süverkrüp+Ahrendt	Operational Determinants	Collaboration of suppliers, adopters and non-adopters
Non-Adopter	Sievers Sanitär	Technology	Creation of a network or community to share insights and experiences
Non-Adopter	Sievers Sanitär	Operational Capacity	Support through external coaches or consultants
Non-Adopter	Sievers Sanitär	Technology	Suppliers need to inform about opportunities and developments
Non-Adopter	Sievers Sanitär	Technology	Software tools to structure and visualize data

Figure 8: Overview of all Solutions of the Barriers of Data Analytics Adoption

To sum up, based on the findings of the empirical in-depth interviews, a basic draft of the determinants of technological innovation adoption on the example of data analytics is visualized in figure 9. This is a first concept and classification of the findings which is enhanced in the end of the chapter 5.

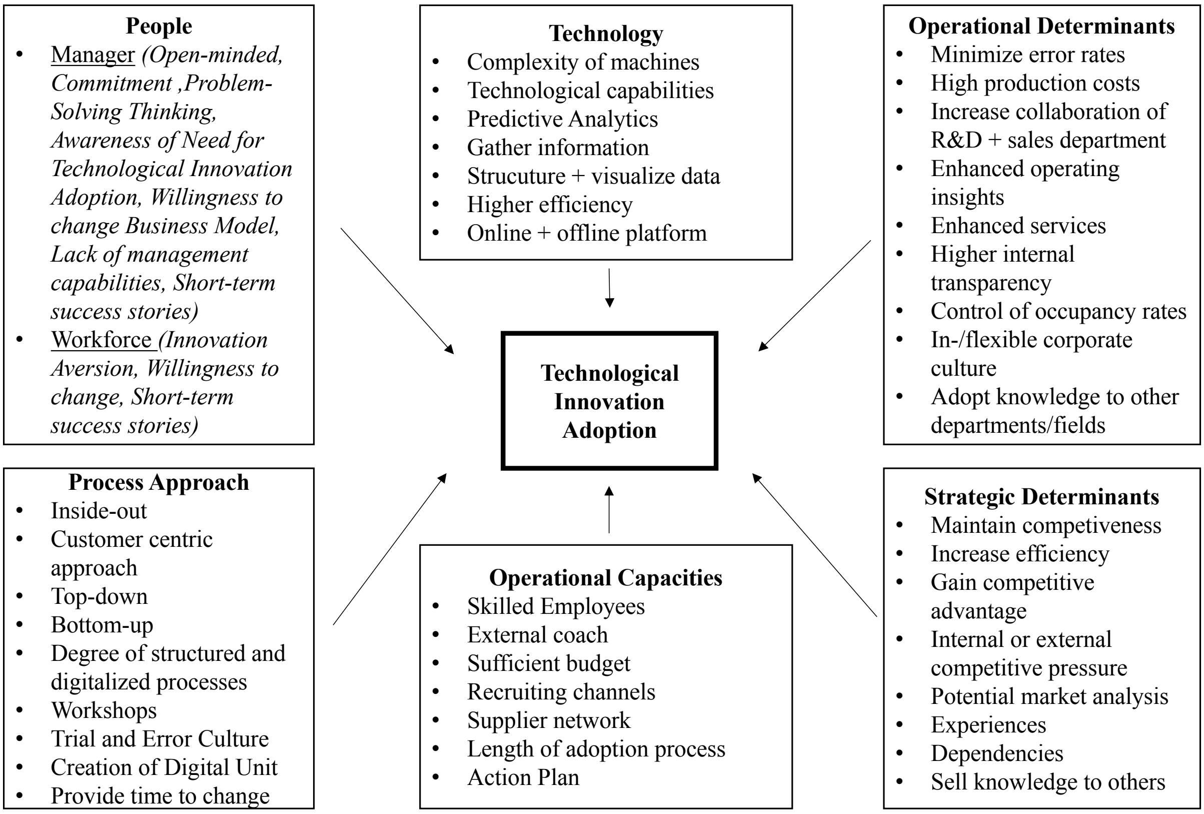

Figure 9: Classification of Determinants of Technological Innovation Adoption based on the empirical findings.

5. Discussion

This chapter aims to interpret the empirical and theoretical findings. By doing so, propositions for further theoretical conclusions are derived. As this is an inductive study, this section is structured as followed (Eisenhardt & Graebner, 2007): Firstly, the empirical findings are discussed. Based on the empirical analysis, a proposition is deduced. Next, a proposition is discussed from a theoretical perspective by reflecting the frameworks for general innovation adoption from the literature review.

Discussing the research question in regard to the reasons for (no) technological innovation adoption, it can be stated that there are a range of diverse intentions among the interviewees. While the non-adopters are generally interested in novel technological innovations, Süverkrüp+Ahrendt and Sievers Sanitär are facing no external nor internal need to adopt data analytics (Dr. Niemann, 2017; Sievers, 2017). Thus, "a better overview about the internal processes and resources as well as better services are desirable, but not mandatory" (Sievers, 2017). The adopters tend to not have an external adoption pressure, but rather innovated due to an internal need for action. Hofrichter (2017) for example, claims to have innovated due to high operating error rates in the ordering process as well as high inefficiencies due to a decentralization of the branches. In addition, Weil (2017) stresses and acknowledges that the current workforce is insufficient skilled to handle the machines, high production costs as well as a climb in labor costs. Organizations primarily face an internal need to adopt which could be satisfied by the internal drivers of data analytics. Thus, the **first proposition** can be stated:

P1: To increase the likelihood of a technological innovation adoption, an internal, operational need of an organization is required.

By referring this proposition to the academic literature about innovation adoption, the first evident difference between innovation and technological innovation adoption arises. Dodgson (2008) emphasizes that innovation adoptions are driven by external and internal factors. Porter (2001) as well as Frambach and Schillewaert (2002) state an organization's need for innovation is primarily driven by environmental changes. This might be caused by business partners which have previously adopted an innovation. According to the adopters within the conducted interviews, technological innovation adoptions, however, tend to have an internal need. Moreover, it can be derived that the non-adopters might have identified a problem, but it is not perceived as relevant or classified to be solved by a technological innovation. This argumentation is supported by Usher (1954).

Through analyzing the barriers stated by the interviewees, it can be gaged that both adopters and non-adopters of data analytics are subjected to the same adoption barriers. The experts highlight the main adoption challenges such as a missing technological understanding of top managers and a lack of willingness to disrupt a business model (Hofrichter, 2017; Dr. Niemann 2017; Redmer, 2017). Furthermore, Sievers (2017) and Weil's (2017) employees have an aversion to technological innovations and are ultimately unwilling to change their routine. From an economical perspective, Hofrichter (2017) and Dr. Niemann (2017) argue that uncertain monetary benefits and high costs lead to no mandatory reason to adopt data analytics. These corporate insights imply that there is no differentiation in terms of barriers for adopter and non-adopter. However, the decision to adopt data analytics might not depend on the amount, complexity or type of barriers but rather on the willingness to solve the stated barriers. This interpretation is supported by the different solutions highlighted by the interviewees. While the non-adopters tend to describe general and obvious solutions for data analytics such as an external coach (Sievers, 2017) or higher profits to reinvest internally (Dr. Niemann, 2017), the adopters are more precise and provide more in-depth answers.

Here, the adopter Weil (2017) requires their employees to develop and define new technology projects in workshops. This trial and error culture lead to high levels of employee commitment and thus, ensures a successful adoption. Here, Hofrichter (2017) underlines the importance of short-term success. Furthermore, Hofrichter (2017) stresses the need for an independent digital unit as otherwise managers tend to interrupt and influence the progress of this unit. These profound in-depth solutions underline that adopters spent more time to analyze potential barriers and how these barriers could be solved. Thus, the **second proposition** is stated:

P2: To increase the likelihood of a technological innovation adoption, high levels of problem-solving thinking are required.

This proposition is applicable to the literature regarding innovation adoption. According to Damanpour and Schneider (2008), pro innovation-oriented managers are more likely to create a facilitating atmosphere. This, however, has a positive impact on the innovation adoption culture. In addition, in terms of innovation characteristics, Damanpour and Schneider (2008) as well as Frambach and Schillewaert (2002) could not find an interplay between complexity and innovation adoption. Consequently, the number and degree of complexity of barriers has no impact on innovation as well as technological innovation adoption. It is more about the relevance and impact of these adoption types (Damanpour & Schneider, 2008). If an adoption is perceived as mandatory, high problem-solving thinking standards are required.

At this point, it is worth to mentioning that the interviewees give insights about the innovation-oriented culture, however, they have not stated the influence of managers' demographic characteristics. Thus, a discussion about the differences between innovation and technological innovation adoption on the influence of age, gender or tenure of the mangers is not possible.

During the adoption stage of a technological innovation, the adopter Hofrichter (2017) stresses that short-term success stories are a driver of data analytics in the adoption stage. Due to high costs and frustration in the beginning of an adoption project, short-term success is important for both employees' and managements' commitment (Hofrichter, 2017). Thus, the **next propositions** are stated:

P3: To increase the likelihood of a technological innovation adoption, short-term success stories are required.

This determinant highlights a difference between innovation and technological innovation adoption as the short-term success is not covered in the innovation adoption frameworks by Frambach and Schillewaert (2002), and Damanpour and Schneider (2008). Thus, a short-term success stories might be specific for technological innovation adoptions.

Referring to the adopters and supplier, an independent digital unit is a key driver for technological innovation adoptions (Hofrichter, 2017; Redmer, 2017; Weil, 2017) Here, Hofrichter (2017) highlights that an independent digital unit has the ability and freedom to define new projects and create the required resources for a technological innovation adoption. Redmer (2017) supports this idea and calls his own solution an "innovation lab" which is responsible for the adoption of technological innovations. Consequently, the **fourth proposition** is developed:

P4: To increase the likelihood of a technological innovation adoption, an independent digital unit is required.

The fourth proposition is not supported by the two academic frameworks of Frambach and Schillewaert (2002), and Damanpour and Schneider (2008). An independent digital unit is therefore a specific determinant of technological innovation adoption.

Lastly, non-adopters request a proactive approach from the suppliers in terms of marketing activities (Dr. Niemann, 2017; Sievers, 2017). This pattern is deduced by the non-adopters which demand suppliers to inform potential adopters (Sievers, 2017) as well as require a better collaboration of suppliers and non-adopters (Dr. Niemann, 2017). The adopters, however, do not depend on the supplier activities as they show higher problem-solving levels as stated in proposition 2. Therefore, the **fifth proposition** is developed:

P5: To increase the likelihood of a technological innovation adoption, marketing activities of suppliers are required.

The demanded supplier marketing activities is evaluated in the innovation adoption framework by Frambach and Schillewaert (2002). They found a significant positive impact of supplier marketing activities on perceived innovation characteristics and thus on innovation adoption. Consequently, there is no difference between innovation and technological innovation adoption. Thus, non-adopters depend on suppliers' promotions regardless of the innovation adoption type.

To summarize and visualize the discussed empirical and theoretical results, a **new framework** is developed (figure 10). This framework is based on the two theoretical frameworks and the classification of the determinants of technological innovation adoption as stated in figure 9. The italic letters are specific technological innovation adoption determinants, while the others are not.

By doing so, the perceived innovation-, managers' personal- as well as adopter characteristics of the frameworks are reduced by the determinants not stated by the interviewees. Consequently, the innovation specific determinants are sorted out while the deduced specific determinants of technological innovation adoption are integrated. The specific determinants are split up in the main characteristics as stated in figure 10, namely managers' personal-, perceived innovation-, and adopter characteristics. Moreover, further developed specifications such as operational- and strategic determinants are supplemented. The supplier marketing activities are maintained. Operational determinants, strategic determinants, and supplier marketing activities are assumed to have a direct effect on the perceived innovation-, managers' personal- as well as adopter characteristics. Here, a positive correlation of supplier marketing activities on perceived innovation characteristics is already tested by Frambach and Schillewaert (2002). This new framework needs to be investigated by further researchers to test the significance of the propositions.

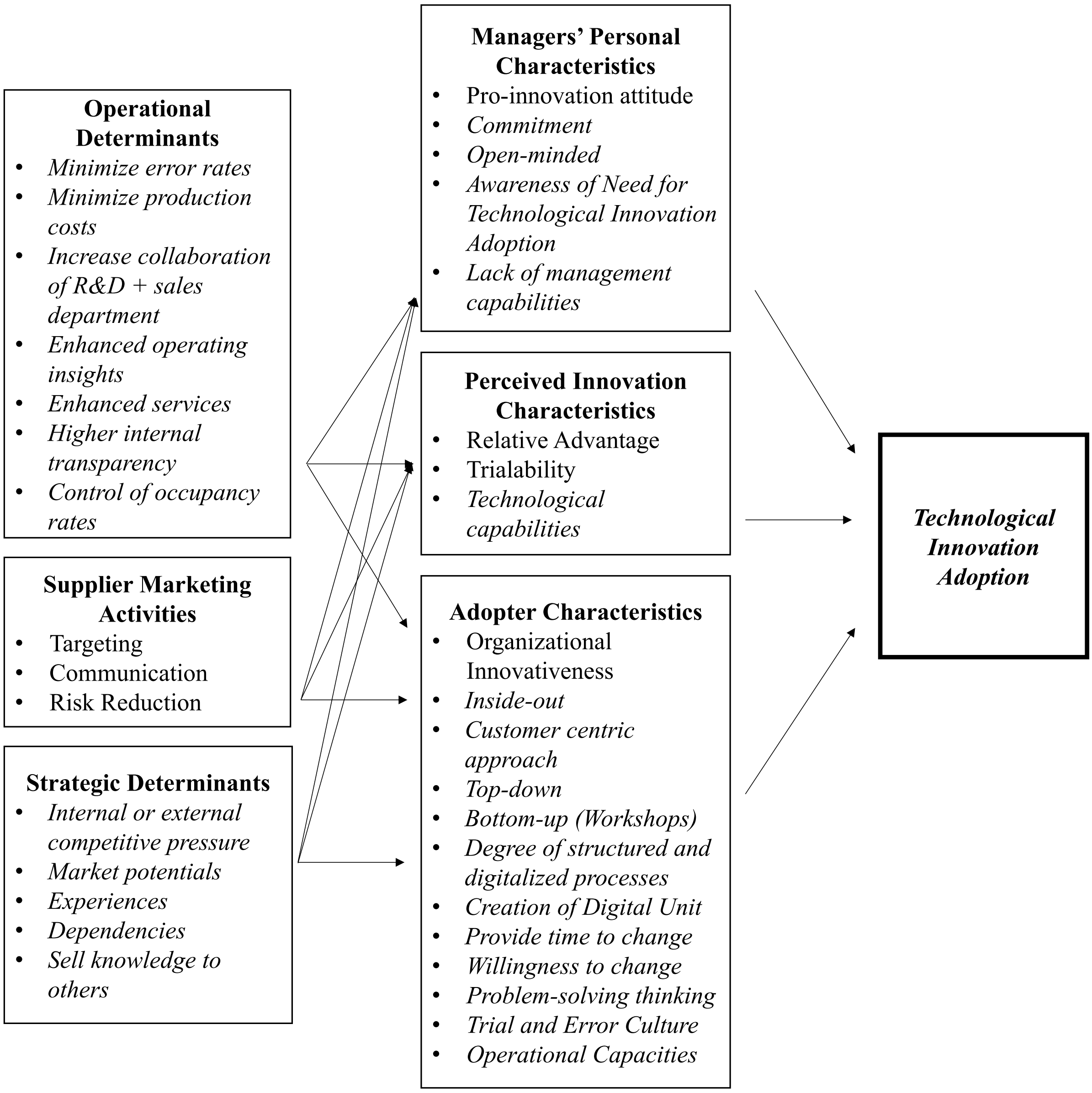

Figure 10: The specific determinants of technological innovation adoption

6. Implications

6.1 Theoretical Implications

This research explores the drivers and barriers of technological innovation adoption using the example of data analytics based on two complementary innovation adoption frameworks. From the results of the conducted research, it can be concluded that there are differences and similarities between the determinants of the different innovation adoption types. Thus, some determinants of the innovation adoption frameworks could be confirmed in the qualitative study while some others not. Starting with the **macro framework** by Damanpour and Schneider (2008), the managers' demographic characteristics are not stated by the interviewees. Thus, it could be assumed that they are not relevant for a technological innovation adoption. This fact is supported by the limitations of Damanpour and Schneider (2008) as the study focuses on administrative and incremental innovations. Additionally, the managers' personal characteristics are partially discussed in the interviews as only the pro-innovation attitude is stressed. Therefore, the significant measured effect on political orientation might be specific for the innovation adoption while pro-innovation orientation is a determinant on both adoption types. Nonetheless, managers' commitment, open-mind, awareness, and management capabilities needs to be added in the technological innovation adoption framework. These determinants are emphasized and perceived as relevant by the interviewees. Moreover, this research categorizes innovation characteristics as innovation adoption specific. Even though Damanpour and Schneider (2008) found a positive effect on cost and no significant result on complexity, this qualitative study evaluates the three innovation characteristics as irrelevant for technological innovation adoption. Here, adopters and non-adopters are facing the same barriers independently on costs or the degree of complexity. To sum up, main parts of the framework by Damanpour and Schneider (2008) might be innovation adoption specific due to the administrative incremental focus.

Referring to the **micro perspective** framework (Frambach & Schillewaert, 2002), a bigger overlap can be found. While the empirical investigation confirms the need of supplier marketing efforts in technological innovation adoption decisions, environmental influences could not be associated to technological innovation adoption. Furthermore, in terms of perceived innovation characteristics, only the relative advantage and trialability are specific for both innovation and technological innovation adoption. Here, the interviewees underline the unforeseeable economical aspect as a barrier. Trialability, however, is assessed as a driver. Compatibility, observability as well as uncertainty might be innovation adoption specific as this could not be interpreted as relevant. In terms of adopter characteristics, only the organizational innovativeness is technological innovation adoption specific. The size and structure of an organization could not be confirmed and might be innovation specific. However, determinants such as operational capacities, the willingness to change or customer centric approach need to be added to a technological innovation adoption framework as they are evaluated as specific determinants for technological innovation adoption. Additionally, the strategic determinants such as market potentials and dependencies as well as operational determinants such as the minimization of error rates and production costs are evaluated as technological innovation adoption specific (figure 10).

6.2 Managerial Implications

This research can be used by managers to ensure a successful technological innovation adoption, since it comprises the differences between adopters and non-adopters as well as the drivers and barriers of a technological innovation adoption. Starting with the implications for the **suppliers**, this research evaluates the importance of supplier marketing activities for non-adopters in order to inform and promote technological innovation solutions. This might be supplemented by an online or offline platform to share experiences (Sievers, 2017). Furthermore, suppliers need to communicate the internal drivers of data analytics as organizations being aware of internal drivers are more likely to adopt.

For the **non-adopter**, however, high problem-solving standards, short-term success stories, a trial and error culture, and the creation of an independent digital unit or innovation lab are key for a successful technological innovation adoption. Nonetheless, **adopters** need to take these determinants into account to increase the efficiency of the adoption process.

In general, this master thesis observes some specific determinants of technological innovation adoption compared to innovation adoption. These need to be considered due to the fact that managers might be familiar with general innovation adoptions. However, by adopting a technological innovation, managers might neglect determinants such as the complexity and costs. Furthermore, external influences, including; the size and structure of an organizations as well as the age, tenure and education of top managers seem to be irrelevant to the technology adoption process.

7. Limitations

No management investigation could be expected to explain all observations made in a study. Thus, it is essential to recognize the limitations of this research.

The thesis conducts qualitative exploratory inductive interviewees in order to investigate an unexplored area by deducing propositions for further theory building (Burns & Burns, 2016; Yin, 2016). However, this research design triggers one limitation automatically. As the statements of the interviewees might be subjective, there might be a problem of generalization due to low standards of reliability and validity (Burns & Burns, 2008). Moreover, the social status, age, gender or educational background might have an effect on the interview. Furthermore, this research is conducted by one individual, namely the author. A one-person study might lead to a monopoly, as the researchers' personal approach does not tend to be controlled by another researcher (Miles and Hubermann,1994). To weaken this argumentation, this research standardized the questionnaires and interviews. According to Yin (2014), this leads to greater reliability. Referring to the selection of interviewees, the amount of five interviews for a qualitative research are reasonable (Yin, 2014). Furthermore, the selection of organizations is based on several parameters such as leading players within an industry. Nonetheless, the results are not generalizable and require quantitative research. Lastly, data analytics is selected as an adequate example of technological innovation adoption. These findings, however, might not be reliable and valid for other technological innovation adoptions.

To sum up, the thesis illuminates a variety of determinants of technological innovation adoption even though it does not claim that the results and findings of this research are the only specific drivers and barriers. However, this study highlights the importance to distinguish between innovation and technological innovation adoption as there are no other examples of management research that could explain these observations stated in this thesis.

8. Further research

With regard to the limitations mentioned above, further research could be conducted. As this thesis has an inductive exploratory approach, further in-depth and quantitative research needs to be done to test the propositions as stated. By doing so, potential theories might be build (Burns & Burns, 2008; Yin, 2014). Furthermore, other scholars need to verify the findings by coding the results again. This increases the validity and reliability of the discussion. In addition, misinterpretations, missed details as well as inadequate sources are avoided (Burns & Burns, 2008). Besides that, further research is needed to change the parameters of the selection of interviewees to verify of the findings. Here, a higher number of suppliers, adopters and non-adopters is recommended.

Moreover, further research is needed to test other technological innovation adoption examples as this research is limited to data analytics. By doing so, the findings and results of this investigation will become more valid and reliable.

According to Frambach and Schillewaert (2002), the reasons for non-adoption may lie at earlier stages of the adoption process.

To sum up, this qualitative exploratory research should encourage other scholars to test the derived propositions and to study the unanswered questions with a multidimensional approach to achieve deeper understanding.

9. Conclusion

The aim of this research is to accomplish an understanding of the determinants of a technological innovation adoption by comparing suppliers, adopters and non-adopters. By doing so, this thesis relates innovation adoption frameworks with the empirical findings of technological innovation adoption to derive specific determinants of the adoption decision. This research demonstrates that organizations specifically adopt technological innovations due to internal, operational needs, while scholars such as Dodgson (2008) and Porter (2001) emphasize that innovation adoptions are driven by external and internal factors. What is more, adopters and non-adopters of technological innovations are facing the same barriers, whereas, adopters show higher levels of problem-solving thinking and thus are more capable to adopt. This highlights that adopters deal with possible barriers and drivers of a technological innovation.

Further specific determinants of a successful technological innovation adoption include; short-term success stories, an independent digital unit which defines and enforce projects as well as supplier marketing activities. In contrast, some theoretical drivers and barriers are solely related to innovation adoption such as managers' demographic- and innovations characteristics as well as environmental influences. Moreover, the significant findings on size, structure, complexity, and compatibility are innovation adoption specific.

In the near future, it remains to be seen how successfully organizations will adopt technological innovation such as data analytics. Even though the potentials to do so are stated, adopters and non-adopters have to unveil the solutions of the adoption barriers of data analytics. This awareness of the organizations determines the pace of the progress.

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Expert Interviews

Jens Redmer, Principle of New Products, EMEA, Google Germany GmbH, conducted on the 3th of November 2017

Gerd Hofrichter, Director Communication, Konditorei Junge GmbH, conducted on the 23th of October 2017

Dr. Wolf-Dieter Niemann, CEO, Süverkrüp+Ahrendt GmbH & Co. KG, conducted on the 19th of November 2017

Christian Sievers, CEO, Sievers Sanitär GmbH, conducted on the 21st of November 2017

Florian Weil, CIO, Weil Engineering GmbH, conducted on the 24th of November 2017

Appendix 2:

Official statement of original paper/report/thesis

By signing this statement, I hereby acknowledge the submitted paper/report/thesis*, titled: Determinants of Technological Innovation Adoption in Organizations - An exploratory study on the example of Data Analytics

to be produced independently by me, without external help.

Wherever I paraphrase or cite literally, a reference to the original source (journal, book, report, internet, etc.) is given.

By signing this statement, I explicitly declare that I am aware of the fraud sanctions as stated in the Education and Examination Regulations (EERs) of the SBE.

Place: Maastricht, NL

Date: 07.04.2018

First and last name: Max Julius Jacobi

Study programme: Double Degree Nova SBE, Maastricht SBE: IB Strategy & Innovation

Course/skill: 2016-600-EBS4025: Skill MA Thesis: IB Strategy

ID number: i6151338

Signature: Max Jacobi

*strikethrough the subjects that are not applicable.

Appendices

Appendix 1: Overview of all key findings

		General Determinants of Technological Innovation Adoption	Reasons for (no) Data Analytics adoption	Drivers of Data Analytics adoption	Barriers of Data Analytics adoption	Solutions for adoption barriers
Supplier	Google Germany	Hire highly qualified employees which define new projects, not v.v.	Companies do not know where and how to start	Open new business markets	Lack of digital education of employees biggest adoption barrier	Provide time for culture change
		Management which supports and anticipates innovation	Collection of data nothing innovative but lower barriers of entry and higher technological standards	Optimize services, predictive services	Underestimation of innovation pressure of top managers	Willingness to change a business model + technology understanding
		Trial and Error Culture	Several benefits such as maintain competitiveness and increase in efficiency	Better understanding of internal processes to derive actions	No willingness to change a business model	Trail and error culture and Innovation Lab
		Short Adoption Processes	Higher efficiency through better technological tools	Change business model disruptively and sustainably for the future	Lack of management capabilities, do not know where and how to start	Investment in own workforce towards advanced and sophisticated employees
Adopter	Konditorei Junge	Could not be conducted	Reduce misplanning of bread and sandwich orders	Minimize errors of order planning	No real economic proof of benefits	Have short-term uccess stories during the adoption process
			Restructuring of branches to categories with the support of a central information system	Gathering more data about customers through prepaid loyalty card	Grown and inflexible corporate structures vs. Start-Up stuctures	Management supports and leads investments
			New competitors: Amazon Fresh	Being first mover increases pressure for competitors	Conservative corporate culture which includes an aversion to innovations	Willingness to adopt Data Analytics holistically
				Strengthen market competiveness	Lack of data analytics understanding	Creation of independant "digital unit"
	Weil Engineering	Close collaboration of R&D and sales department	Insufficient skilled employees	Minimize errors of checklists	Badly structured and non-digitalized processes	First, structure processes, then digitalization
		Customer centric approach to identify new needs	Operation of machines is becoming more complex, as the systems are more complex	Adapt solutions and knowledge to other machines	Which data/What is the value/Where to source?	Workshops with employees which define projects to great acceptance
		Definition, market analysis, technological requirements, concept and prototyping stage	High labor costs	Better data to derive decisions	Missing measurement unit standards	Prototyping based on trial and error
		Trial and Error Culture	High production costs	Sell knowledge about cloud solutions to others	Different backgrounds of employees which avoid changes in their routines	Have short-term success stories
Non-Adopter	Süverkrüp+Ahrendt	Need to create new resource capacities for innovations	Just started to critical look at chances and challenges	Legal generation of data about customers	Workforce fears changes and try to avoid technological innovation	Be open-minded for new developments and innovations
		Sufficient skilled employees	Dependency on Mercedes Benz	Better understanding of customers' needs	Automotive suppliers own the generated data	Reinvest profits internally (e.g. in processes and employees)
		Potentially: recruiting of new employees	First, structuring of internal data, then data analytics adoption	Support decision-making process	Missing data analytics understanding of top managers	Improve collaboration with Mercedes Benz
		Intelligent collaboration of departments	Other operating priorities	Improve and optimize internal supply chain	Lack of human capacities	Internal collaboration within departments
		Technological capabilities insufficient in the company for a successful adoption process	No competitive pressure to adopt		No real economic pressure to invest	Collaboration of suppliers, users and potential users
	Sievers Sanitär	Chronological and analytical order how to adopt an innovation	Just started to critical look at drivers and barriers	Higher transparency about internal processes and resources	Employees have reservations and fears of contact	Creation of a network or community to share insights and experiences
		Analyze market and targets before investing	Missing own experience	Better use of resources (budget, employees)	Do not know how and where to gather data and information	Support through external coaches or consultants
		Adapt internal processes to enable innovations	Missing market experience	Better control of occupancy rates	Do not know suppliers of Data Analytics to start adoption	Suppliers need to inform about opportunities and developments
		Skilled and capable employees	No network or community to get information	Improve general decision-making	High Costs --> No real economic proof of benefits	Software tools to structure and visualize data
		Support through third parties such as suppliers	No need to adopt		No operating capabities	

Appendix 2: Questionnaire Supplier

Questionnaire for an empirical survey of a Master thesis at the

Strategy & Organization department

"Drivers and Barriers of Technological Innovation Adoption in Organizations -
An exploratory study on the example of Data Analytics"

1. In general, which determinants are required for a technological innovation adoption?
2. Why your clients adopted Data Analytics?
3. What are the general drivers of Data Analytics adoption?
4. What are the general barriers of Data Analytics adoption?
5. How can these barriers be solved?
6. What are the key success factors for data analytics adoption?

Appendix 3: Questionnaire Adopter

Questionnaire for an empirical survey of a Master thesis at the

Strategy & Organization department

"Drivers and Barriers of Technological Innovation Adoption in Organizations -
An exploratory study on the example of Data Analytics"

1. What are the general determinants required for a technological innovation adoption?
2. Have you already adopted Data Analytics?
3. Why have you already adopted Data Analytics?
4. What are the chances of Data Analytics adoption?
5. What are the barriers of Data Analytics adoption?
6. How can these barriers be solved?
7. What are the key success factors for data analytics adoption?

Appendix 4: Questionnaire Non-Adopter

Maastricht University

NOVA School of Business & Economics

Shaping powerful minds

Questionnaire for an empirical survey of a Master thesis at the

Strategy & Organization department

"Drivers and Barriers of Technological Innovation Adoption in Organizations -
An exploratory study on the example of Data Analytics"

1. What are general determinants required for a technological innovation adoption?
2. Have you already adopted Data Analytics?
3. Why have you not adopted Data Analytics?
4. What are the barriers of Data Analytics adoption?
5. How can these barriers be solved?
6. What are the drivers of Data Analytics adoption for your organization?

AACSB ACCREDITED ASSOCIATION AMBA ACCREDITED EFMD EQUIS ACCREDITED

Appendix 5: Transcription of Interview with Supplier

Interview with Google Germany GmbH

The interview is conducted with Mr. Jens Redmer, Principle of New Products for EMEA countries via WhatsApp call on the 3th of November 2017. The interview is conducted in German and translated in English by the interviewer. Redmer agrees to publish his statements and allowed the interviewer to quote his answers.

Interviewer: Hello Mr. Redmer, thank you very much for your time. I am glad to have Google as an interview partner for my thesis. Should we directly start, or do you have any questions beforehand?

Redmer: Hello Mr. Jacobi, you are more than welcome! No, I have no questions, thanks!

Interviewer: Okay great, so why clients have adopted data analytics?

Redmer: Honestly, companies have insufficiently adopted in data analytics. Often, top managers are lacking the understanding of this innovation or do not know how to start. In general, business intelligence is nothing brand new. We already generated data in the history. However, the new thing is the amount and quality of data. Obviously, the benefits are higher efficiency rates, vaster production adaptions through new technical tools and maintain competiveness.

Interviewer: Very interesting! Okay, so what are the drivers of data analytics?

Redmer: This question, I want to answer with the help of the example of John Deere. Do you know John Deere?

Interviewer: Yes, of course, the agriculture machinery manufacturer!

Redmer: Yes, so they put sensors on their agriculture machinery in order to document abrasion etc. By doing so, they are able to predict the possibility of a service and can schedule an appointment with their clients in advance. In the past, clients called their machinery suppliers when they had the need for a service. Nowadays, John Deere changed their business model from a reactive to a proactive approach and are now able to predict a service. By doing so, they are able to call an engineer and schedule a service while knowing that it is raining outside, or the farmer cannot work due to several reasons. John Deere is no longer thinking about how to shorten the reaction period for a service, rather they are trying to prevent services. Moreover, they have several new insights of their machinery. For example, as they have better insights about their service periods, they have the ability to exhaust the limits for a potential new service. Finally, it needs to be stated that John Deere is no longer an agriculture machinery manufacturer, but rather an interdisciplinary data analytics player. Another similar example is the construction industry. Here, data analytics could be used for the coordination of a fleet of a company with the help of drones. Drones are counting and locating vehicles and analyzing a better economic use. This analysis would be directly communicated to the vehicles and would have a direct impact on the coordination of the fleet. Another example is the automobile industry. Here, machine learning is based on data analytics which can improve materials sciences. However, I wanted to highlight the benefits and chances of data analytics with the help of these examples. So, benefits are independent of a family or non-family business: new business areas, optimization of services, better understanding of corporate insights. Consequently, "stupid" companies are getting advanced and sophisticated. One example for the last bullet point is Klöckner GmbH. This company is specialized in steel trading. Since they implemented data analytics applications, they exactly know who, when and what is ordered. With these insights, they realized an online market opportunity for small order amounts. In the beginning, they suffered profitability problems, however, with the help of data analytics, they become economical and got a better understanding of its customers. When, a company does not have the know-how, it can rent or buy technical solutions. Here, one example are cloud solutions which for example analyses pictures and logos and afterwards advise where and when to promote a picture or logo. Clouds solutions are in general the programming interface in order to directly forward documents. Here, the barriers of entry are lower than in the past and the development is rapid which leads to the fact that companies have the capabilities to focus more on their business. Here, one example is that questionnaires and documents can be easily translated in different languages.

Interviewer: Wow, these are a lot of insights! Thank you very much, especially for the visualization! But what are the barriers?

Redmer: To put is straight the biggest barrier is the digital education of the people. So consequently, companies have no workforce to implement data analytics. Secondly, companies still do not understand that digitalization is not a trend, it is reality. Therefore, many companies are losing time and might lose their competitive advantage. Thirdly, often companies don't have the willingness to change. However, even if companies realized that they need to adapt their business model, they don't know how to start which is a huge barrier, too.

Interviewer: Okay, obviously there are a lot of barriers, but how could these be solved?

Redmer: I think the solution of barriers requires time. So, companies need time to develop a culture change. Secondly, top managers need to show high levels of willingness to change a business model. Top managers are key as they have to disrupt their old business model in a consequent way. Moreover, they need to implement a problem-solving thinking culture and a better understanding of services. At this point, I would like to mention Volkswagen. They try to develop a service which activates additional engine power if demanded for a specific time. Consequently, a customer doesn't have to go to a branch and rent a car with a bigger engine for a weekend. They just have to send a message to request this service. This would be a disruption. Last but not least, companies have to invest in their own employees in order to ensure a high quality.

Interviewer: Wow, so there are a lot of potential solutions for the barriers. What would be interesting next is what general determinants are required for successful adoption?

Redmer: So, as I already mentioned, highly educated workforce is key. This education needs to be scaled. Furthermore, companies need to rethink their hiring strategy. First, they need to hire highly sophisticated employees who afterwards define new projects, and not the other way around! Thirdly, management is an important resource. Manager need to endorse innovations and see digitalization as a change. Here, an external consultant might be helpful. Fourthly, short implementation periods are needed as the implementation of projects took years or months in the past. However, nowadays, the product lifecycle is much shorter. On the other side, old processes need to be refined without losing the focus on the main business. Furthermore, inter department communication and collaboration is key. When we are talking about processes, it is important to incorporate a failing culture. Innovations are strategic, therefore an innovation lap might be helpful.

Interviewer: Okay, great, these are a lot of information! Maybe you can quickly summarize the key determinants for a technological innovation adoption....

Redmer: Yes sure, so basically as I mentioned earlier, companies need to hire external and fresh employees. Companies have to rethink their recruiting strategy and hire experts first and define new projects afterwards. In addition, companies have to invest and educate their workforce. Fourthly, companies have to create a corporate failing culture and reduce the levels of fears in case of a failure. Lastly, the management needs to show willingness to change.

Interviewer: Thank you Mr. Redmer for your short summary and for all your valuable insights! It was a pleasure to interview you!

Redmer: Awesome! You are more than welcome. Good luck with your thesis.

Appendix 6: Transcription of Interview with Adopter

Interview with Konditorei Junge GmbH

The interview is conducted with Mr. Gerd Hofrichter, Director of Communications via telephone call on the 23th of October 2017. The interview is conducted in German and translated in English by the interviewer. Mr. Hofrichter agreed to publish his statements and allowed the interviewer to quote his answers.

Interviewer: Hello Hr. Hofrichter, thank you very much for your time. I am glad to have Konditorei Junge as an interview partner for my thesis. Should we directly start, or do you have any questions beforehand?

Hofrichter: Hello Mr. Jacobi, you are more than welcome! No, I have no questions, thanks!

Interviewer: Okay, great so, may you can introduce your adopted data analytics project

Hofrichter: Yes sure, we as a company have been collected data since ten years in order to generate insights and make consequently a better decision. Here, we basically focus on the internal POS (point of sale) system. Historically, we are able to collect the price, time and product number of a purchase and consequently know which products is bought most on which days. But the question is what we can learn as admittedly, our ordering process error rate was very bad. This is why we developed our own central information system made by Junge. Currently, we employ 20 IT people to run this system. We realized that in history store managers ordered bread and sandwiches based on the gut instinct. But today, our ordering process depends on 50 different variables such as the date or weather. Due to a high transparent and central approach, we are able to cluster similar stores and build categories depending on the revenue or characteristics of customers. This, however, has consequences for all of us. And most importantly to our employees which did not trust this central system in the beginning. They argued that top managers or the central order system itself do not know the customer. Another example is the change of opening hours. In the past, each store manager changed the opening hours manually, however, today, in case of a change, there is an automatic process to order a new signage or to change the opening hours on the homepage. Everything is online and centralized. But at this point I have to mention that even though you might think that we are pioneers and first movers, we are at the very beginning of data analytics. We have not started to integrate a CRM system. So, there is a lot to do.

Interviewer: Okay wow, this is very interesting. So, what are the drivers of data analytics adoption?

Hofrichter: Mainly, there are two drivers: reduction of errors and an increase in efficiency due to shorter communication. Another driver is our prepaid loyalty card. In the past, customers could collect loyalty points, but we had no information about the person himself. Now, we are offering that customers can use this loyalty card as a prepaid card after a short online registration. This gives us a lot more information, however, as I mentioned earlier, our CRM system is not very good yet. But we do not want to outsource this topic. What I basically wanted to say is that disruptive innovations lead to new competitiveness. Amazon fresh and home delivery are only a few examples. But we try to see innovations as a driver to get better instead of fearing the future.

Interviewer: Okay, valuable insights. So, what are the barriers of data analytics adoption?

Hofrichter: One barrier are legal issues. Who is legally responsible for the delivery for example? In addition, an internal barrier is the investment itself. You cannot really measure the benefits in the beginning and manager only see the costs. Thirdly, especially family businesses have a conservative mentality and culture compared to other countries such as the U.S. This argument is supported by the fact that many companies have an aversion against new things and want to stick to old processes and products. Maybe this depends on grown corporate structures and consequently on the age of a company. Of course, an old company has a grown organization which might be an advantage, however, on the other side this leads to the fact that structures are inflexible and need more time to change than start-ups for example. By the way processes, another barrier is that a company has to change completely its business model. So, many managers might avoid such a risk, especially when a company has not really the need to disrupt a well working structure. Additionally, in case you want to benefit from data analytics, departments have to work together. Departments are not separated anymore, it is about the process and the progress of a project. This is why we would characterize ourselves as a IT company which sells buns and sandwiches. However, this supports my statement above. Normally in companies, each department works on its own. So here, there is a need for a huge change again which leads to unforeseeable risks and costs.

Interviewer: Okay great, so what are the solutions for the barriers?

Hofrichter: This is not easy to say, otherwise we would have solved it. But in general, I think it is important to implement data analytics disruptively. A company needs an own unit, let's call it 'digital unit' which is responsible for all digital implementations. Moreover, this unit needs to be independent of other departments. Another solution is a mental change on top management levels. The top management needs to be convinced of data analytics and patient about the implementation.

Interviewer: Okay, so we more or less started to talk about the key success factors...
Hofrichter: Yes, you are right, the solutions for the barriers might be key success factors. But I want to add that willingness of change is definitely key. For top managers but for ‘normal’ employees as well. In addition, the independency of the digital unit... without independence it will not work as other departments tend to focus to much on their perspectives. And lastly it is important to have short-term success. This is important in order to justify further investments.
Interviewer: Great, do you have anything to add?
Hofrichter: No, this is it.
Interviewer: Okay, thank you very much for your time and valuable insights! I highly appreciate to interviewed you!
Hofrichter: You are welcome. Good luck with your thesis.

Interview with Weil Engineering GmbH.

The interview is conducted with Mr. Florian Weil, project manager of Industry 4.0 via telephone call on the 28th of October 2017. The interview is conducted in German and translated in English by the interviewer. Mr. Weil agreed to publish his statements and allowed the interviewer to quote his answers.

Interviewer: Good evening Mr. Weil, thank you very much for your time. I am glad to have Weil Engineering as an interview partner for my thesis. Should we directly start, or do you have any questions beforehand?
Weil: Hello Mr. Jacobi, you are more than welcome! No, I have no questions, thanks!
Interviewer: Great, so let’s start with the first question.
Weil: Yes, so basically, we try to work closely with our clients. By doing so, we want to develop and achieve new innovations. So, while having a customer centric approach, our R&D department collaborates closely with our sales department. If a new order has technological barriers, then firstly, I try to analyze if this new solution has a potential market. If no, we will reject the order. If yes, we have three stages, namely a definition, technical and concept stage. Starting with the first one, we make a cost calculation and ask if the client is willing to pay our price. If yes, we are thinking about the development and construction of this new machine solution. Furthermore, we are thinking about the requirements and needs, technical tolerances as well as materials. In a last step, we are developing a concept including a rapid prototype. These three stages are based on trial and error. We want to have a quick prototype and feedback loop of the client which allows us to improve our new solution service within the development.

Interviewer: Great, thank you! So, let's have a deeper look on technological innovations, namely data analytics. May you can introduce your adopted data analytics project?

Weil: A few years ago, we started to put sensors on our machines. These sensors are sending data to a cloud with a specific information. After a sensor reports an error, we are trying to analyze why this sensor was triggered. Was it the sensor itself or a specific problem? If there is a problem, we can help our customers immediately. One example is the vibration at a shaft. After the commissioning, the vibration will be calibrated. If the error is too big, the sensor will report it to the cloud. By doing so, we are able to predict a service or shift service intervals. Additionally, we are able to make conclusions for new innovations. Talking about the prediction of services, it is important to mention that we are able to analyze the real occupancy rate. Often, customers do not know the real occupancy and thus there are wrong maintenance frequencies. But with sensors and a cloud solution, we can determine the exact operating time and consequently, predict the next service. In a next step, to improve this process and the interpretation of data, we need better algorithm. These algorithms are required for irregularities.

Interviewer: Wow, this is a lot of valuable information! So why you decided to adopt sensors and cloud solutions?

Weil: There are basically four reasons. Firstly, the operation of plants is becoming more complex as the systems are getting more complex. Secondly, the production costs are increasing. In the past, costs were divided by 60% mechanic costs and 30% electronic and sensor technology costs. However, today this ratio changed to 50/50. So, we are facing an increase in sensor and electronic costs while prices remain the same. Thirdly, we have more complex systems and no skilled employees to run the machines. In the past, in case of an emergency, we had one expert who could fix every problem. However, today we retrain people with a completely different background. They are able to run a system but in case of an error, they are not able to fix it. Therefore, we need the technology. Lastly, we need to decrease our labor costs.

Interviewer: Thank you for your insights! What are the drivers of data analytics adoption?

Weil: Well, in the past, our experts had checklists. But these checks were done irregularly and insufficiently. Thus, there were many errors in these checklists. Today, we are more human independent. The sensors are reporting everything with a significant smaller error rate. Consequently, we have better and more reliable data to derive decisions. Furthermore, we are able to sell the improved knowledge to our customers. Moreover, we are technological able to adopt this knowledge to other machines or sell our know-how to other companies. Another driver is to increase the level of delivery reliability. Due to the fact that we are working for automotive manufacturers, we are seeking to deliver our services just in time. By the way, often our customers are required to deliver just in time, too. By doing so, a client and its ERP system has access to our machines. So just imagen there is a new order, the production needs to be planned and the process time is two weeks. But the product is needed in four weeks. In general, often, the newest order will be produced first but this is highly costs intensive. However, based on a well working ERP system, I am able to update my client about the production progress and increase the delivery reliability.

Interviewer: Thanks, very interesting! So, what are the barriers of data analytics adoption?

Weil: It is all about the data. It is difficult the identify the right data and afterwards report the relevant data in the cloud. So, what are my selection criteria, what is my value, what is relevant and where am I procuring the data? But before thinking about data and technological innovation, it is crucial to have well-structured processes. It makes no sense to digitalize a badly structured process. And then, there is the problem of measurement units, especially in terms of international businesses. Imagen an American client uploads data in the cloud about the temperature of a machine, there will be a high error rate in the interpretation in Germany due to different measurement units. Another barrier are employees. Often, they have different backgrounds and ideas of the implementation of innovations. But I want to highlight that my personal experience is that employees are not afraid of losing their job due to the new technical developments. And they don’t have to. Fortunately, we have a lot to do and need more capacities. Technological innovation could help us to continue our growth. So currently, everyone is very busy and appreciate some help.

Interviewer: Okay great, so how could these barriers be solved?

Weil: So, regarding the measurement units, we need intelligent algorithm who convert different units into one standard unit. Here, we developed a data tool to standardize measurement units before reporting the information to the cloud. Secondly, in terms of employees, we want to implement innovations by workshops. So, while our employees are working in workshops and thinking about drivers of a development, they start to identify themselves with these new projects. I know that as a manager, it takes more time than a top-down approach, but this approach is more efficient in the long-run. Furthermore, I want them to develop small prototypes. It is not about the perfect solution after a week, it is about a trial and error approach and the incorporation of feedback.

Interviewer: Okay, very nice! So, when you summarize the key determinants for a successful data analytics adoption. What are they?

Weil: Most importantly, the acceptance of the employees. They need to show the willingness to adapt an innovation. They need to be convinced of the corporate strategy. Otherwise, they are working for the wrong company. Secondly, it is crucial to have small and short-term success stories. I prefer to have a weekly meeting and see the progress of a project rather than one meeting after three months. Of course, this is more stressful, but you have a better control and more success. Lastly, the top management needs to believe in technological innovation adoptions. There will be the day, where deadlines will not be matched, or the project requires a bigger budget. In this case, it is crucial that top managers are convinced of the strategy and provide more time or monetary resources. Here, often managers made this experience in other projects for example in the acquisition of a client and managers tend to provide more resources. However, in technological innovation projects, managers might avoid further investments as they only see the costs.

Interviewer: Great, do you have anything to add?

Weil: No, this is it.

Interviewer: Okay, thank you very much for your time and valuable insights! I highly appreciate to interviewed you!

Weil: You are welcome. Good luck with your thesis!

Appendix 7: Transcription of Interview with Non-Adopter

Interview with Süverkrüp+Ahrendt GmbH & Co. KG

The interview is conducted with Mr. Dr. Wolf-Dieter Niemann, CEO, via telephone call on the 19th of November 2017. The interview is conducted in German and translated in English by the interviewer. Dr. Niemann **did not** agreed to publish his statements, however, allowed the interviewer to quote his answers.

Interviewer: Good morning Dr. Niemann, thank you very much for taking your time especially during the weekend! I highly appreciate it.

Dr. Niemann: Good morning Mr. Jacobi, you are welcome!

Interviewer: So, do you have any questions regarding the topic or agenda of today?

Dr. Niemann: No, thanks. I think I had enough time to think about your questions.

Interviewer: Okay great, so let’s start with the first question. What are the general determinants of a technological innovation adoption

Dr. Niemann: So, in terms of resources, our business model is highly human intensive. We employ 30 people only in services and sales. This is a lot. So, for an innovation we need to generate new capacities. One solution would be to hire even more people, however, this is highly cost intense. Another solution would be to have a more efficient collaboration of our current workforce. This would generate new capacities which can be used to work on something new or generate even more revenue by increase the service level for our customers. However, sometimes our employees are a barrier. People avoid changes. Often, the workers' council inhibits developments or new innovations. Nevertheless, the first position and job description of a new hire will not be the same over the years. So, we are constantly developing our employees. Therefore, changes are a normal process. However, in terms of processes, I cannot really make a statement as we are lacking fundamental technical knowledge for our innovation processes. And I do not know where to hire or get this know-how. Often, when you want to cooperate with big players such as Salesforce or Google, you completely lose your data. This is not what we want and try to avoid.

Interviewer: Okay, so now let's have a closer look and let's go a little bit more into detail. Have you already adopted data analytics, besides general technological innovation adoption?

Dr. Niemann: To put it short, no!

Interviewer: Okay and why not?

Dr. Niemann: Adoptions are a process. We are currently starting to think about the potentials and barriers of data analytics. In general, compared to other competitors in our sector, we are highly innovative and belong to the top 10%. But again, we are depending on Mercedes Benz. Another point is that we have to structure internal data in the first place, have to define technological innovation processes and afterwards we are able to generate capacities. A third point are other priorities. Before investing in data analytics, we need a well-designed website or an improvement in our business development center for customer inquiries. But at this point, I need to highlight the advantage of a family business and SMEs. We are working independently of our priorities even though we are lacking human capacities. We prefer to finish a process to 100% and in a proper way. A last point is that the pressure is relatively low to invest in data analytics.

Interviewer: So, you already touched the next question but more precisely, what are the barriers?

Dr. Niemann: Yes, to put it short there are three things: we are lacking an implementation understanding of data analytics projects, we do not have the human capacities, and lastly, we do not have enough pressure from the market to invest in this area.

Interviewer: Okay, and how do you want to solve these barriers?

Dr. Niemann: The best thing would be if everyone would buy more Mercedes Benz vehicles in one of our stores. We would increase revenues and consequently our profit. This would lead to new investments in employees or technical standards as the money often will be reinvested in the company. This is another typical family business characteristic.

Interviewer: Okay, but let's take a look on the other side: what are the drivers of data analytics adoption?

Dr. Niemann: Honestly, I need to know more about all the market opportunities to give a an proper answer. So how can I get the data legally, what do suppliers supply? But in general, one driver is a better understanding of our customers' needs in terms of mobility. Another driver is to redefine our supply chain. Due to technological innovation we have new competitors such as wirkaufendeinauto.de, a start-up which enters the market and sells and buys cars online. The same thing happened to other industries such as to the hotel or plane business. But the question is: how can we benefit from these developments? And what is our competitive advantage compared to the start-ups?

Interviewer: Thank you, so let's talk about the last question...

Dr. Niemann: Okay, so first of all, technological innovations and data analytics are not a trend, it is reality. This is important to understand and a first key success factor. Secondly, a company needs to be open-minded and keeps its eyes open for new innovations. Thirdly, it is about the timing of an investment. If you invest too early, it costs a lot of money. But if you invest too late, it costs the market. Lastly, it is about collaboration. Suppliers need to understand that the corporate culture of its clients and the users need to think about data analytics. By doing so, both can learn from each other and will have success stories.

Interviewer: Great, do you have anything to add?

Dr. Niemann: No, this is it.

Interviewer: Okay, thank you very much Dr. Niemann for your time and valuable insights! I highly appreciate to interviewed you! Dr. Niemann: You are welcome. Good luck with your thesis.

Interview with Sievers Sanitär GmbH

The interview is conducted with Mr. Christian Sievers, CEO, via telephone call on the 23th of November 2017. The interview is conducted in German and translated in English by the interviewer. Mr. Sievers agreed to publish his statements and allowed the interviewer to quote his answers.

Interviewer: Hello Mr. Sievers, thank you for taking your time and answering my questions today! Do you have any questions before we start?

Sievers: Hello Mr. Jacobi, sure, you are welcome! I am looking forward to answering your questions. No, if you like, we can directly start.

Interviewer: Okay great, so what are the general determinants requires for a technological innovation adoption?

Sievers: First, we need capable and skilled employees who are able to define, analyze and implement innovations. Second, these employees need a sufficient budget. In terms of processes, it is highly important and key to thing about the internal as well as external integration of this innovation. So, what I want to say is that this innovation has a significant impact on your internal processes. So how should you adapt it and what is even more important, before thinking about an innovation, you have to analyze the market size. I want to give you an example. A few years ago, I flew to Mexico to buy a new and innovative bathroom furnishing. However, back in Germany, while I tried to sell it to my customers, I realized that there is no need for this furnishing even though I was highly convinced of this innovation. So, my conclusion is that you have to ask yourself if you need a market first before you invest or if you have to invest first and then create a new market.

Interviewer: Okay, very interesting. You already made a good transition to the next question. Have you already adopted data analytics?

Sievers: No, I mean, the last example would be a good beginning for a data analytics adoption. In case of a drop-in sales, which we can realized with the help of data analytics software, we are able to boost our marketing campaigns. But again, I think this is very fundamental and basic. So, we need to improve this.

Interviewer: Okay, and why have you not adopted data analytics yet?

Sievers: The answer is very simple. I have reservations and fears of contact. I do not know what I can expect, and I cannot define the unforeseeable risks. I have no personal experience with such a huge innovation and even the market experience is very small. So, I do not have a network or people to ask. Next, I do not know where to get the software and hardware for data analytics implementations. And of course, the costs for investments might be very high without even know the real drivers and potentials of such an investment.

Interviewer: You touched many points...but how do you want to solve these barriers?

Sievers: As I said, I am in a very early stage of this innovation and I have not really thought about an investment. Therefore, first, I need a network, partner or other companies to talk about data analytics. It is important to have a conversation and share experiences with others. The next step is the support of an external coach or consultant. I do not have the operating capabilities to do that on my own.

Interviewer: Okay, so what are the drivers of a data analytics adoption?

Sievers: Definitely a better planning of resources in terms of money and employees. On the other side, we could have a better control of our occupancy rates. So, in general, we have a higher transparency of internal processes and resources which lead to better insights of our operating business. This, however, directly effects our decision-making. For example, we could optimize our procurement in terms of supplier negotiations or a better product selection.

Interviewer: Okay, so when you think about the key success factors for data analytics adoption process. Which fundamental things are required?

Sievers: The most important thing is software. We need an outstanding and easy handling software which analyses and visualizes our data. So, the software is more like a tool to derive correct decision for our whole supply chain. I see a lot of potentials for the optimization of our fleet management. Currently, we have 20 cars. But we do not really know how, who, when, and where they are used. The same thing with our machine tools. If we have a better understanding of the utilization and higher transparency, we could make better decisions in procurement, maintenance etc.

Interviewer: Okay, thank you very much for your answer. Do you want to add anything?

Sievers: You are welcome! No thanks, if I missed something, I will drop you a line.

Interviewer: Okay, thank you very much for your time and valuable insights! I highly appreciate to interviewed you!

Sievers: You are welcome. Good luck with your thesis.